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China's industrial carbon emissions: Historical drivers at the regional and sectoral levels and projections in light of policy targets

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Chapter 1

General introduction

1.1. Background

The Paris Agreement of 2015 aims to hold the global average temperature increase to well below 2 °C above pre-industrial levels and pursue efforts to limit this to 1.5 °C (UNFCCC, 2015). The cumulative CO_2 emissions have been identified to be near-linear with global mean temperature change by several studies (Allen et al., 2009; Matthews et al., 2009; Meinshausen et al., 2009). Even though the global CO_2 emissions from fossil fuels remained stable from 2013 to 2016 with values of 32.29-32.32 $GtCO_2$/yr, the cumulative emissions still keep increasing. In order to meet the goals of Paris Agreement, the emissions should be reduced rapidly until zero emissions (Peters et al., 2017). China has a crucial role to play in realizing such climate ambitions. Since the reform and opening up in 1978, China's economy has developed rapidly, exhibiting strong rates of urbanization and industrialization. China's economic development depends strongly on energy consumption, especially fossil energy. The fossil energy consumption accounted for 88.9% of national energy consumption in 2016, generating a large amount of CO_2 emissions (IEA, 2018). China's CO_2 emissions experienced rapid growth since 2002, surpassing the USA to become the largest CO_2 emitter in the world in 2007 (IEA, 2017). In response to climate change, China made a commitment at the Copenhagen Conference, in 2009, that carbon intensity should decrease by 40-45% in 2020 when compared to the 2005 level (NDRC, 2010). Further targets were then made for intermediate steps towards 2020, and further reductions by 2030, achieving 60-65% reductions by 2030 over a 2005 baseline and reaching the emissions peak by 2030 or even earlier (INDCs, 2015). From 2013 to 2016, the CO_2 emissions of China decreased from 9.53 $GtCO_2$/yr to 9.2 $GtCO_2$/yr, which was caused by a shift in economic structure, a change in the energy mix, and improvement of energy efficiency (Guan et al., 2018).

The industrial sector is the pillar of China's economic development. The share of industrial value added (IVA) in China's GDP is around 40% (NBSC, 2001-2016b). Industrial energy consumption increased from 707 Mtce/yr (million tons of coal equivalent) in 2000 to 2196 Mtce/yr in 2015, accounting for almost 68% of national energy consumption (NBSC, 2001-2016a). This energy consumption is largely coal-based and led to a large amount of CO_2 emissions, with coal-based emissions representing up to about 84% of national CO_2 emissions in 2015 (Shan et al., 2018). This large share of industrial emissions has led policy makers to enact industry-specific policy targets, in addition to setting targets for emissions reduction at national level: 34% decrease in industrial energy intensity from 2015 to 2025; 40% decrease in industrial carbon intensity from 2015 to 2025; 3% increase (from 12% to 15%) in low-carbon energy consumption from 2015 to 2020; 2.8% decrease (from 27.8% to 25%) in the share of IVA of six energy-intensive industries in total IVA; 4.7% increase (increase from 5.3% to 10%) in share of green manufacturing output (SC, 2015; MIIT, 2016). Given the large share of China in global carbon emissions, and the dominant role of the industrial sector in China's emissions reduction efforts, studying industrial energy consumption and CO_2 emissions is crucial to understand how to achieve the emissions reduction of China and whether China can achieve the emission targets set at national and international levels.

1.2. Approaches to account for CO_2 emissions

There are two commonly used methods to estimate CO_2 emissions, namely production-based and consumption-based approaches (Peters, 2008). The production-based accounting (PBA) calculates CO_2 emissions considering the direct energy consumption by the producer (including exports), so PBA can identify the key emitters (e.g., nations or industries) who generate the emissions directly and find the ways to reduce emissions from the production side, such as improve the energy efficiency using clean production technologies. Compared to PBA, the consumption-based accounting (CBA) estimates the CO_2 emissions of products consumed including imports, where the indirect emissions embodied in the trade can be revealed and consumers' responsibilities for environmental burdens can be identified (Mi et al., 2019; Liang et al., 2017b). CBA can support policy decisions related to consumption behaviors and international collaboration. Therefore, the PBA focuses on the direct emitters while CBA focus on the final consumers. Usually, it will make a difference in emissions when using different approaches (Liang et al., 2017a). In order to better enable producers and consumers to shoulder the responsibilities of emissions reduction in addressing the climate change, studies have been conducted from both production and consumption perspectives for policy supports (Liang et al., 2017a; Liang et al., 2017b).

Globally, the United Nations Framework Convention on Climate Change (UNFCCC) used PBA approach to assess the impact of each country on climate change caused by greenhouse gas (GHG) emissions, so that the emissions reduction targets can be developed (Gavrilova and Vilu, 2012). Additionally, the current UN emissions allocation system for greenhouse gases attributes emissions to countries in which emissions physically generated during production (Steininger et al., 2015). Against this background, the commitment of China's emissions reduction targets to the Copenhagen conference and Paris Agreement were based on PBA. In order to address the emissions reduction of China's critical industry and make a connection with China's emission goals, the CO_2 emissions in this thesis refer to the production-based emissions.

1.3. Historical evolution of industrial energy consumption and CO_2 emissions

Energy consumption is one of the major sources for CO_2 emissions and has been causally linked to economic development in China (Mi et al., 2018). China's industrial output grew rapidly from 2000 to 2015, exhibiting a fivefold increase. Along with this, there was a substantial increase in industrial energy consumption, with an average annual growth rate of 9.9% since 2000 (NBSC, 2001-2016a). The fraction of coal consumption in China's energy mix increased from 56.68% in 2000 to 65.24% in 2010 and decreased thereafter to 59.32% in 2015. The industrial energy consumption exhibited growth before 2013 and declined in 2014 and 2015. However, the industrial energy intensity decreased from 0.18 Mtce/billion yuan in 2000 to 0.13 Mtce/billion yuan in 2015 (in 2000 constant prices). Along with the rise in energy consumption, China's industrial CO_2 emissions increased with an annual growth rate of 9.7% during the period of 2000-2013 (from 2.5 $GtCO_2$/yr to 8.2 $GtCO_2$/yr). They declined by 1.7% and 3.2% in 2014 and 2015, respectively. The industrial carbon intensity experienced a decrease from 0.61 Mt/billion yuan in 2000 to 0.45 Mt/billion yuan in 2015 (in 2000 constant prices). The significant changes in energy consumption/intensity and CO_2 emissions/intensity prompts important questions about what factors caused such changes.

Considerable progress has been made in developing a better understanding of how economic activities and their development are related to changes in carbon emissions (Rosa and Dietz, 2012). A crucial area in this research field is to analyze the driving forces that influence the evolution of energy consumption or CO_2 emissions. A better understanding of these driving drivers is critical to formulate policies for emissions reduction and targets achievement (Wang et al., 2017). The examination of the drivers of CO_2 emissions has been conducted by scholars from various perspectives, such as economics, political science and sociology (Rosa and Dietz, 2012). Next to studies analyzing historical drivers of carbon emissions, studies that analyze future trends in emissions are also important in assessing if existing carbon reduction policies are sufficient to realize emissions pledges such as INDCs (Intended Nationally Determined Contributions) and global emission targets.

1.4. Drivers of changes in carbon/energy intensity

As discussed in section 1.2, the driving forces of industrial CO_2 emissions and energy use are of great importance. China covers a vast geographical territory with significant regional differences in natural resource endowments and levels of industrialization and economic development. This suggests that there may be important regional differences in the factors driving the industrial CO_2 emissions. Furthermore, according to China's Industrial Classification for National Economic Activities in 2017, the industrial sector can be divided into 42 sub-sectors. The contribution to the aggregated industrial carbon emissions may vary across sub-sectors. So, when conducting the studies on energy consumption and CO_2 emissions at the national level of China, the differences at provincial and sectoral levels should be taken into account. In the following sections, therefore the regional heterogeneities in carbon/energy intensity and sectoral heterogeneities in carbon/energy intensity will be addressed.

1.4.1 Regional heterogeneity in carbon intensity

China's manufacturing is concentrated in eastern China in industrial clusters near coastal cities, which are thriving centers of industrial production for the export of goods. Simultaneously, the inland provinces have developed metallurgy, mining, and other resource-intensive industries (IEA, 2017). For example, Guangdong is a province which mainly focuses on clothing, electronics, toys and food. Hebei has abundant iron ore and oil resources. Jiangsu, Shanghai and Zhejiang are three important comprehensive industry provinces in China. Xinjiang, Shanxi and Inner Mongolia are the most important provinces extracting primary energy carriers such as coal. Thus, given such crucial differences in industry structure, the industrial CO_2 emissions are likely to vary significantly across provinces. In 2015, the top three provinces by absolute CO_2 emissions were Shandong, Jiangsu and Hebei, with values 173.5%, 159.6% and 145.8% higher than the national average. Conversely, the industrial absolute CO_2 emissions in Hainan, Beijing and Qinghai were 11.7%, 14.4% and 15.5% of the national average level (CEADs, 2018).

In 2015, industrial carbon intensity varied from 0.1 Mt/billion yuan in Beijing to 2.1 Mt/billion yuan in Xinjiang (CEADs, 2018; NBSC, 2016b). The provinces in the central and northwest regions had higher emission intensities, whereas the provinces in the eastern coastal areas had lower intensities. Shandong, Jiangsu, Guangdong and Zhejiang are the provinces which had absolute CO_2 emissions higher than the national average level while their carbon intensity (Mt/billion yuan) was lower than the average level. On the other hand, the carbon intensity also changed over time for all provinces. From 2000 to 2015, the industrial carbon intensity decreased by 83% in Beijing while it increased by 53% in Xinjiang. Against this background, it is important to compare the industrial carbon intensity as well as the driving forces that influence industrial carbon intensity over time across provinces.

Several studies have explored the driving forces of industrial CO_2 emissions/intensity in a time series of multiple provinces (Zhou et al., 2017; Wang and Feng, 2017; Wang et al., 2018a). However, in those studies changes in CO_2 emissions/intensity are obtained on the basis of the emissions/intensity in the observed year and previous year, which can only address the temporal characteristics for each province. In view of the regional heterogeneities in carbon intensity, the spatial comparison is also worth investigating. Therefore, an additional study that can simultaneously capture the spatial and temporal differences in carbon intensity and its driving forces is of great importance (Chapter 2).

1.4.2 Sectoral heterogeneity in energy intensity

Rapid economic growth allowed for very high rates of capital stock improvement and renewal, and the installation of modern and energy-efficient equipment for capacity additions has also increased over the past few years. The industrial aggregate energy intensity of China has improved significantly from 2000 to 2015: it is half of what it was in 2000. The energy intensity of the steel sector, for example, was reduced by 74.7% between 2000 and 2015 (NBSC, 2001-2016a; NBSC, 2001-2016b). The diversity of manufacturing processes, ranging from the very energy-intensive electricity, steel, cement and chemicals sub-sectors to non-energy-intensive sub-sectors such as electronics fabrication, presents a substantial variation in an assessment of the energy intensity of the industrial sector. For example, in 2015 the energy intensity varied from 0.51Mtce/billion yuan in the *petroleum* sector to 0.002 Mtce/billion yuan in the *tobacco* sector (in 2000 constant prices) (NBSC, 2001-2016a; NBSC, 2001-2016b).

Heavy capital investment has been the main driver for the rapid economic growth of China over the past few decades, with the R&D expenditure and fixed asset investment in industrial sector increasing almost tenfold (NBSC, 2001-2016b). Energy intensity has been identified as the most important factor causing the decline of industrial carbon intensity (Wang et al., 2018a; Wang and Feng, 2017; Zhou et al., 2017). The R&D expenditure and fixed asset investment always go hand in hand with the commercial scale and technology progress, and are identified as factors that may affect the energy efficiency/intensity. (Shao et al., 2016; Zhang et al., 2017). However, it is unclear what role the investment played in industrial energy intensity with each sub-sector although Guan et al. (2014) pointed out that the intensive investment may lead to an increase in national carbon intensity. Therefore, it is important to conduct an analysis exploring the driving forces of industrial aggregate energy intensity, especially the factors related to the R&D expenditure and investment. If a sectoral perspective is taken, more details can be provided for policy makers. Several previous studies have conducted studies on the drivers of industrial CO_2 emissions from a sectoral perspective (i.e., Wu and Huo, 2014; Liu et al., 2015), but they failed to consider the technological factors. It will help us to further improve the energy efficiency and avoid over-investment when the technological factors and the contribution of each industrial sub-sector to the industrial aggregate indicator are taken into account.

1.4.3 Methods for identifying the drivers of CO_2 emissions

Decomposition analysis is one of the most commonly used method to analyze the drivers for changes in carbon emissions (Ang and Choi, 1997). A decomposition analysis essentially assigns changes in an aggregate metrics into components related to several candidate drivers, and the results are usually used to explain the contribution of the candidate drivers to the observed changes in the aggregate indicator. The most popular decomposition methods are IDA (index decomposition analysis) and

SDA (structural decomposition analysis) (Hoekstra and van den Bergh, 2003). Although both IDA and SDA are used to understand the determinants of the CO_2 emissions/intensity, their origins and methodological foundations are different. IDA is usually based on the activity and emissions data, which usually can be easily obtained and employed in both historical and future analyses. Studies in continuous time series has always been common since the continuous data for these indicators are usually available. However, the SDA is often based on input-output (IO) tables and has relatively high data requirements (Wang et al., 2017). Data for continuous years is usually not available because benchmark IO tables are published with gaps of several years (Su and Ang, 2012). As far as the study objective is concerned, if the focus is the energy end-use sector or a national level, IDA is a good choice. The data set on end-use energy and output both in the aggregate level and its components can be derived. This is an advantage of IDA analysis since energy policy implications always aim at end-use sectors. However, if the supply and demand relationships of an economy or the embodied energy/emissions are of interest, SDA should be a priority since it could model the whole economic system (Wang et al., 2017).

Another commonly used method to identify the drivers of environmental indicators is the IPAT formula, where the environmental impacts (I) can be presented as: I= Population (P) × Affluence (A) × Technology (T) (Ehrlich and Holdren, 1971). Using the IPAT formula as the theoretical basis, the STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) model was proposed (Dietz and Rosa, 1994), which is a stochastic model and can be used to identify the non-proportionate impacts of factors or variables on environment (Shao et al., 2011). In empirical studies, the STIRPAT is always used combining with econometric techniques (Lin et al., 2017). The results of a decomposition analysis can be used to reflect the observed changes in CO_2 emissions caused by a certain driver, while the results of STIRPAT can only identify the elasticity coefficients between CO_2 emissions and the drivers for the study period.

In this thesis, the index decomposition analysis was used because the end-use sector (industrial sector), the yearly change of industrial carbon/energy intensity and the contribution of the drivers are the subjects of interest.

1.5. Debate on whether China can achieve the emissions goals

China set the goal to reduce her carbon intensity by 40-45% in 2020 and 60-65% in 2030 compared to 2005, and to achieve a peak in carbon emissions by 2030 or before (NDRC, 2010; INDCs, 2015). In recent years, a large number of studies have discussed whether China can achieve these 2020 and 2030 emissions goals. Some of them pointed out that China can achieve the reduction targets of carbon intensity with current policies (Xu et al., 2017; Zhang et al., 2017), while others pointed out that the ongoing policy framework is not sufficient to meet the goals (Yuan et al., 2012; Elzen et al., 2016). Besides, some studies suggested that China cannot reach the emissions peak in 2030 in the business as usual scenario (Yu et al., 2018) while others thought that the emissions peak can be achieved in 2030 or even earlier (Hao and Wei, 2015; den Elzen et al., 2016; Niu et al., 2016).

Previous studies were mainly based on the major drivers of CO_2 emissions, such as economic output, energy structure, energy intensity (efficiency) and industrial structure, to project the CO_2 emissions for China as a whole, a specific region or a specific industry (e.g., Zhu et al., 2018; Zhang et al., 2017; Wu and Peng, 2016). However such studies paid little attention to regional heterogeneities or convergence. At the same time, several studies showed that the CO_2 emissions per capita tend to converge across different provinces (Wang and Zhang 2014; Zhao et al., 2015). Indeed, for a specific industrial sub-sector, since technological features are similar, one can expect that regional convergence will take place over time due to technology adoption and diffusion (Gries et al., 2018). As discussed before, the industrial sector played a crucial role in China's the economic development but also in the rise of China's carbon emissions. Energy-intensive industries accounted for almost 90% of industrial emissions. Therefore, regional convergence of energy efficiency and carbon emissions in China's energy-intensive industries will be of great significance for China's future CO_2 emissions and related emissions goals.

As discussed before, the driving forces of the historical evolution of industrial energy consumption and CO_2 emissions in China have been studied extensively (see section 1.3). Besides, there are many studies that focused on the projections of CO_2 emissions in the industrial sector and its major sub-sectors (e.g., energy-intensive industries) using different scenario assumptions, to investigate future trajectories and whether the emissions peak can be realized in 2030 (e.g., Wang et al., 2016; Zhao et al., 2018; An et al., 2018; Gao et al., 2017). Research on the driving forces can help us understand which factors contributed to decrease in CO_2 emissions in the past while the projections of CO_2 emissions can tell us the possible way to achieve the emissions goals. There are many strong and frequent policies in China, connecting with which can help us to better understand the historical drivers and scenario assumptions in projections. Therefore, a more systematic summary of previous studies is urgently required to investigate the changes in patterns of drivers, the possible range of the industrial CO_2 emissions and policy goals. The lessons learned from the efforts on industrial emissions reduction of China can indicate how China can contribute to the emission reductions agreed upon in Paris Agreement.

1.6. Research questions

As discussed above, the industrial sector accounted for about 84% of national emissions in 2015, so the industrial CO_2 emissions play a crucial role if China is to achieve its national and internationally pledged carbon reduction goals. The main research question posed in this thesis is hence: *Has the industrial sector in China effectively been decarbonizing in recent years, across different regions and subsectors, and is it plausible that it will reduce its CO_2 emissions in conformity with national and internationally pledged emission goals?*

Tracking the progress of decarbonization in China's industrial sector towards emissions targets requires studies from different perspectives, related to more specific research questions outlined below.

First, unsurprisingly for a country of the size like China, there are major differences in economic development, demographic trends and resource availability across provinces, which result in the uneven distribution of specific industrial activities across the various provinces. Thus, shaping provincial policies for emissions reduction will be an important component for national policies. In view of heterogeneities across provinces the first specific research question is:

SQ1. *What are the spatial differences in carbon intensity across the provinces in China? What are the differences in driving forces across provinces? What patterns will emerge in the spatial clusters formed when provinces are grouped using spatial autocorrelation?*

When answering this first question, the energy intensity appeared to be the determining factor explaining the industrial carbon intensity for all the provinces in China. Therefore the factors driving the industrial energy intensity was of high relevance. At the same time, the industrial sector can be split into various sub-sectors in relation to the different manufacturing processes. It is hence important to capture the characteristics of the different industrial sub-sectors, to provide sector-specific policy recommendations. Against this background, the second specific research question can be formulated:

SQ2. *What factors drive the changes in aggregate energy intensity of the industrial sector? What is the contribution of industrial sub-sectors to the changes in aggregate energy intensity?*

To answer the question if China can achieve the 2020 and 2030 carbon emissions goals, the future trajectory of CO_2 emissions should be further addressed. Here, the fact that different provinces show different carbon intensities by sector is of interest. A convergence of carbon intensity within similar sectors can be expected: worse performers who have relatively higher carbon intensity in due time are likely to catch up with the better performers (with lower carbon intensity), which can be achieved by technology adoption and diffusion. There are six energy-intensive sub-sectors in the industrial sector that play a very important role in industrial energy consumption and emissions. Motivated by this, the third specific research question is formulated as follows:

SQ3. *What is the contribution of regional convergence in energy-intensive industries to CO_2 emissions reduction and to the emissions goals of China?*

Finally, a large number of studies have been done into the historical development and future developments into the industrial CO_2 emissions of China. One important research stream consists of studies analyzing the driving forces of historical changes in emissions. Another research focus concerns the projections of CO_2 emissions in industrial sector and its major sub-sectors. Furthermore, China has developed a large number and strong policy initiatives to reduce industrial CO_2 emissions. However, there exist no systematic review that relates historical drivers, future projections, and policy interventions focused on industrial CO_2 emissions in China. Against this background, the last specific research question can be formulated:

SQ4. *What are the patterns of historical drivers for the changes in industrial CO_2 emissions in China as identified in the existing scientific literature? What projections for future CO_2 emissions of industrial sector and its major sub-sectors are provided in the scientific literature? And how will policy goals affect the industrial emissions in the future?*

In sum, the overall objective of this dissertation is to study the industrial CO_2 emissions of China, especially in the driving forces of their historical changes, as well as projections of the contribution of industrial sector to China's 2020 and 2030 emissions goals. Through the systematic analysis of the historical data and the existing literature on this topic, policy recommendations can be proposed for China to mitigate global climate change.

1.7. Guide to this thesis

This thesis consists of 6 chapters. This first chapter gives a general introduction, in which the motivation, the research questions and the outline of this thesis are provided.

Chapter 2 discusses the first research question. It identifies the driving forces of industrial carbon intensity using a spatiotemporal logarithmic Divisia index decomposition analysis which integrates spatial and temporal analyses together. By comparing the carbon intensity and its determinants (energy intensity, energy structure and emission coefficient) in different provinces to the national average over time, it can be used to analyze how important different determinants were by province. Besides, spatial autocorrelation is used to aggregate the thirty provinces into four clusters, which are used to address the question of how the presence of neighbors with different (or the same) level of economic development (and its evolution) affects the industrial aggregate carbon intensity.

Chapter 3 sheds light on the impacts of both macro and technological factors on the industrial aggregate energy intensity, and hence discusses the 2^{nd} research question. The macro factors are sectoral energy intensity and industrial structure, while the technological factors refer to R&D efficiency, R&D intensity and investment intensity. Based on the decomposition results, an attribution analysis is conducted to identify the detailed relationship between the influencing factors and sub-sectors, which is significant to assist policymaking since the sensitivity and adaptability of industrial sub-sectors to energy and environmental policies are different. The results thus obtained can be used to test the effectiveness of energy-related policies specified for certain sub-sectors.

Chapter 4 focuses on research question 3, and answers how regional convergence in each energy-intensive sub-sector will impact CO_2 emissions and contribute to meeting the 2020 and 2030 emissions targets. Three scenarios are developed: a business-as-usual (BAU) scenario, which is used to reflect the historical regional convergence; a frontier scenario, which is obtained from the DEA (data envelopment analysis) results and reflects a weak form of regional convergence; and a best available scenario, which refers to a strong form of regional convergence. The CO_2 emissions of each energy-intensive sub-sector are predicted based on the Kaya identity within these three scenarios. By comparing the results in three scenarios, the contribution of regional convergence to the emissions goals can be obtained.

Chapter 5 answers research question 4. It conducts a systematic literature review, focusing on the historical drivers, projections and policy goals of CO_2 emissions in the industrial sector and its major sub-sectors. The drivers of historical emissions, the possible ranges of CO_2 emissions until 2050 in different studies and the policy targets in recent policies are discussed.

Chapter 6 presents a synthesis of the answers to the research questions, followed by a general discussion and outlook for future work.

References

Allen MR, Frame DJ, Huntingford C, Jones CD, Lowe JA, Meinshausen M, Meinshausen N, 2009. Warming caused by cumulative carbon emissions towards the trillionth tonne. Nature 458: 1163-1166.

An R, Yu B, Li R, Wei YM, 2018. Potential of energy savings and CO_2 emission reduction in China's iron and steel industry. Applied Energy 226: 862-880.

Ang BW, Choi KH, 1997. Decomposition of aggregate energy and gas emission intensities for industry: a refined Divisia index method. Energy 18: 59-73.

China Emission Accounts & Datasets (CEADs), 2018. Available from: <http://www.ceads.net/>.

den Elzen M, Fekete H, Höhne N, Admiraal A, Forsell N, Hof AF, Olivier JG, Roelfsema M, van Soest H, 2016. Greenhouse gas emissions from current and enhanced policies of China until 2030: can emissions peak before 2030? Energy Policy 89: 224-236.

Dietz T, Rosa EA, 1994. Rethinking the environmental impacts of population, affluence and technology. Human Ecology Review 1: 277-300.

Ehrlich PR, Holdren JP, 1971. Impact of population growth. Science 171(3977): 1212-1217.

Elzen MD, Fekete H, Höhne N, Admiraal A, Forsell N, Hof AF, Olivier JGJ, Roelfsema M, van Soest H., 2016. Greenhouse gas emissions from current and enhanced policies of China until 2030: Can emissions peak before 2030? Energy Policy 89: 224-236.

Gao TM, Shen L, Shen M, Liu LT, Chen FN, Gao L, 2017. Evolution and projection of CO_2 emissions for China's cement industry from 1980 to 2020. Renewable & Sustainable Energy Reviews 74: 522-537.

Gavrilova O, Vilu R, 2012. Production-based and consumption-based national greenhouse gas inventories: An implication for Estonia. Ecological Economics 75: 161-173.

Gries T, Grundmann R, Palnau I, Redlin M, 2018. Technology diffusion, international integration and participation in developing economies - a review of major concepts and findings. International Economics & Economic Policy 15(1): 215-253.

Guan DB, Klasen S, Hubacek K, Feng KS, Liu Z, He KB, Geng Y, Zhang Q, 2014. Determinants of stagnating carbon intensity in China. Nature Climate Change 4: 1017-1023.

Guan DB, Meng J, Reiner DM, Zhang N, Shan YL, Mi ZF, Shao S, Liu Z, Zhang Q, Davis SJ, 2018. Structural decline in China's CO_2 emissions through transitions in industry and energy system. Nature Geoscience 11: 551-555.

Hao, Y., Wei, Y.M., 2015. When does the turning point in China's CO_2 emissions occur? Results based on the Green Solow model. Environment and Development Economics 20: 723-745.

Hoekstra R, Bergh J, 2003. Comparing structural and index decomposition analysis. Energy Economics 25: 39-64.

Intended Nationally Determined Contributions (INDCs), 2015. Available from: <https://unfccc.int/process/the-paris-agreement/what-is-the-paris-agreement>.

International Energy Agency (IEA), 2017. Global Energy & CO_2 Status Report 2017 <https://www.iea.org/geco/>.

International Energy Agency (IEA), 2018. World Energy Balances. Available from: < https://www.iea.org/statistics/?country=CHINA&year=2016&category=Key indicators&indicator=TPESbySource&mode=chart&categoryBrowse=true&dataTable=BALANCES&showDataTable=false >.

Liang S, Qu S, Zhu AQ, Guan DB, Xu M, 2017a. Income-based greenhouse gas emissions of nations. Environmental Science & Technology 51: 346-355.

Liang S, Wang YF, Zhang C, Xu M, Yang ZF, Liu WD, Liu HG, Chiu ASF, 2017b. Final production-based emissions of regions in China. Economic System Research 30(1): 18-36.

Lin SF, Wang SY, Marinova D, Zhao DT, Hong J, 2017. Impacts of urbanization and real economic development on CO_2 emissions in non-high income countries: Empirical research based on the extended STIRPAT model. Journal of Cleaner Production 166: 952-966.

Liu N, Ma ZJ. Kang JD, 2015. Changes in carbon intensity in China's industrial sector: decomposition and attribution analysis. Energy Policy 87: 28-38.

Matthews H, Gillett N, Stott P, Zickfeld K, 2009. The proportionality of global warming to cumulative carbon emissions. Nature 459: 829-832.

Meinshausen M, Meinshausen N, Hare W, Raper SCB, Frieler K, Knutti R, Frame DJ, Allen MR, 2009. Greenhouse-gas emission targets for limiting global warming to 2°C. Nature 458, 1158-1162.

Mi ZF, Zheng JL, Meng J, Shan YL, Zheng HR, Ou JM, Guan DB, Wei YM, 2018. China's energy consumption in the new normal. Earth's Future 6: 1007-1016.

Mi ZF, Zheng JL, Meng J, Zheng HR, Li X, Coffman DM, et al., 2019. Carbon emissions of cities from a consumption-based perspective. Applied Energy 235: 509-518.

Ministry of Industry and Information Technology (MIIT), 2016. Industrial Green Development Plan (2016-2020). Available from: <http://www.miit.gov.cn/n1146295/n1652858/n1652930/n3757016/c5143553/content.html>.

National Bureau of Statistics of China (NBSC), 2001-2016a. Chinese Statistics Yearbook. China Statistics, Beijing.

National Bureau of Statistics of China (NBSC), 2001-2016b. Chinese Energy Statistics Yearbook. China Statistics, Beijing.

National Development and Reform Commission of China (NDRC), 2010. Available from: <http://unfccc.int/files/meetings/cop_15/copenhagen_accord/application/pdf/chinacphaccord_app2.pdf>.

Niu S, Liu Y, Ding Y, Qu W, 2016. China' s energy systems transformation and emissions peak. Renew. Sustainable Energy Reviews 58: 782-795.

Peters GP, 2008. From production-based to consumption-based national emission inventories. Ecological Economics 65: 13-23.

Peters GP, Andrew RM, Canadell JG, Fuss S, Jackson RB, Korsbakken JL, Quere CL, Nakicenovic N, 2017. Key indicators to track current progress and future ambition of the Paris Agreement. Nature Climate Change 7: 118-122.

Rosa EA, Dietz T, 2012. Human drivers of national greenhouse-gas emissions. Nature Climate Change 2: 581-586.

Shan YL, Guan DB, Zheng HR, Ou JM, Li Y, Meng J, Mi ZF, Liu Z, Zhang Q, 2018. China CO_2 emission accounts 1997-2015. Scientific Data 5: 170201.

Shao S, Yang LL, Gan C, Gan CH, Cao JH, Geng Y, Guan DB, 2016. Using an extended LMDI model to explore techno-economic drivers of energy-related industrial CO_2, emission changes: a case study for Shanghai (China). Renewable & Sustainable Energy Reviews 55: 516-536.

Shao S, Yang LL, Yu MB, Yu ML, 2011. Estimation, characteristics, and determinants of energy-related industrial CO_2 emissions in Shanghai (China), 1994-2009. Energy Policy 39: 6476-6494.

State Council (SC), 2015. Made in China 2025. Available from: <http://www.miit.gov.cn/n973401/n1234620/index.html>.

Steininger KW, Lininger C, Meyer LH, Muñoz P, Schinko T, 2015. Multiple carbon accounting to support just and effective climate policies. Nature climate change 6(1): 35-41.

Su B, Ang BW, 2012. Structural decomposition analysis applied to energy and emissions: Some methodological developments. Energy Economics 34: 177-188.

United Nations Framework Convention on Climate Change, (UNFCCC) 2015. Available from: <https://unfccc.int/sites/default/files/english_paris_agreement.pdf.>

Wang H, Ang BW, Su B, 2017. Assessing drivers of economy-wide energy use and emissions: IDA versus SDA. Energy Policy 107: 585-599.

Wang J, Zhang KZ, 2014. Convergence of carbon dioxide emissions in different sectors in China. Energy 65: 605-611.

Wang J, Zhao T, Wang YN, 2016. How to achieve the 2020 and 2030 emissions targets of China: Evidencce from high, mid, and low energy-consumption industrial sub-sectors. Atmospheric Environment 145: 280-292.

Wang M, Feng C, 2017. Understanding China's industrial CO_2 emissions: a comprehensive decomposition framework. Journal of Cleaner Production 166: 1335-1346.

Wang QW, Hang Y, Su B, Zhou P, 2018a. Contributions to sector-level carbon intensity change: an integrated decomposition analysis. Energy Economics 70: 12-25.

Wu L, Huo H, 2014. Energy efficiency achievements in China’s industrial and transport sectors: how do they rate? Energy Policy 73: 38-46.

Wu QL, Peng CY, 2016. Scenario analysis of carbon emissions of China’s electric power industry up to 2030. Energies 9(12): 988-1005.

Xu L, Chen N, Chen Z., 2017. Will China make a difference in its carbon intensity reduction targets by 2020 and 2030? Applied Energy 203: 874-882.

Yu SW, Zheng SH, Li X, 2018. The achievement of the carbon emissions peak in China: The role of energy consumption structure optimization. Energy economics 74: 693-707.

Yuan J, Hou Y, Xu M., 2012. China's 2020 carbon intensity target: Consistency, implementations, and policy implications. Renewable and Sustainable Energy Reviews 16: 4970-4981.

Zhang X, Zhao X, Jiang Z, Shao S, 2017. How to achieve the 2030 CO_2 emission-reduction targets for China's industrial sector: Retrospective decomposition and prospective trajectories. Global Environmental Change 44: 83-97.

Zhao X, Burnett JW, Lacombe DJ, 2015. Province-level convergence of China’s carbon dioxide emissions. Applied Energy 150:286-295.

Zhao Y.H., Li H., Xiao Y.L., Liu Y., Cao Y., Zhang Z.H., Wang S., Zhang Y.F., Ahmad A., 2018. Scenario analysis of the carbon pricing policy in China's power sector through 2050: Based on an improved CGE model. Ecological Indicators 85, 352-366.

Zhou X, Zhang M, Zhou MH, Zhou M, 2017. A comparative study on decoupling relationship and influence factors between China’s regional economic development and industrial energy-related carbon emissions. Journal of Cleaner Production 142: 783-800.

Zhu BZ, Jiang MX, Wang KF, Chevallier JL, Wang P, Wei YM, 2018. On the road to China's 2020 carbon intensity target from the perspective of “double control”. Energy Policy 119: 377-387.

Chapter 2

An empirical spatiotemporal decomposition analysis of carbon intensity in China's industrial sector[1]

Abstract: In order to develop efficient industrial CO_2 emissions' strategies for China, it is important to compare the performance of carbon intensity and its major driving factors among different provinces. However, such studies are relatively limited so far. The present study describes the features of industrial aggregate carbon intensity (IACI) as well as its driving factors for China's thirty provinces based on the spatiotemporal logarithmic mean Divisia index (ST-LMDI) method. This method allows comparing all provinces against a common benchmark. The empirical results show that Beijing, Tianjin, Shanghai, Guangdong and Heilongjiang rank as the top five provinces while Hebei, Shanxi, Inner Mongolia, Ningxia and Xinjiang perform the worst. From 1999 to 2015, the IACI of most industrial sectors tends to decrease except in Ningxia and Xinjiang, with energy intensity playing a decisive role in all provinces, and both energy structure and emission coefficients yielding mixed effects across provinces and over time. Additionally, this study employs spatial autocorrelation to divide China's thirty provinces into four categories, combining the economic development level and geographical location into a common framework. Then the ST-LMDI method is used to explore how the four regions perform in IACI when the influences of neighbors are taken into account. The results show that the regions with high level of economic development perform better and the regions with the same level of economic development but which are surrounded by less-developed regions have lower IACI. Based on the results, differentiated policies in energy intensity, energy structure and emission coefficient for the local and central governments are recommended.

Keywords: Carbon intensity; China's industrial sector; Provincial disparity; Spatiotemporal decomposition analysis; Spatial autocorrelation.

2.1. Introduction

Since the reform and opening up of China in 1978, China experienced strong economic growth accompanied by a large increase in energy consumption and CO_2 emissions. As a pillar of China's economic development, the industrial sector played an important role in this expansion even though the share of IVA (industrial value added) in GDP decreased slightly from 39.77% in 1999 to 34.32% in 2015 (current price) (NBSC, 2016b). From 1999 to 2015, industrial energy consumption increased from 907.97 to 2922 Mtce/yr (Million tons coal equivalent) and accounted for 67.99% of the national energy consumption in 2015 (NBSC, 2000-2016a). The corresponding industrial CO_2 emissions from

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fossil fuel consumption rose from 2119 Mt/yr in 1999 to 6253 Mt/yr in 2015, contributing to approximately 69.16% of national total emissions. In order to respond to the climate change caused by greenhouse gas (GHG) emissions, the Ministry of Industry and Information Technology of China published the "China Industrial Green Development Plan 2016-2020", aiming to reduce the industrial aggregate energy intensity (industrial energy consumption per unit of IVA) and industrial aggregate carbon intensity (or IACI, measured by industrial CO_2 emissions per unit of IVA) by 18% and 22% in 2020 compared with the 2015 level. Because large variations in the growth patterns of CO_2 emissions and economic development at provincial level exist, the authors of this study believe it is important to identify the factors driving the IACI at both provincial and regional levels to find effective measures for carbon intensity mitigation.

The main objectives of this paper are as follows. First, the present study uses a spatiotemporal logarithmic mean Divisia index (ST-LMDI) (Ang et al., 2016), which integrates spatial and temporal analyses in a single analytical framework, to disentangle the IACI of China's thirty provinces into energy intensity, energy structure and emission coefficient effects. Because the changes in provincial IACI and their underlying driving forces are calculated on the basis of a common benchmark, this study allows for a more accurate comparison of those drivers across provinces over time. Second, spatial autocorrelation is used to aggregate the thirty provinces into four regions and explore their IACI as well, in order to better depict the interaction among adjacent provinces. Finally, some targeted policy implications for local government and central government are provided.

The rest of this paper is organized as follows. Section 2.2 reviews the existing literature. Section 2.3 introduces the decomposition analysis and data sources. Section 2.4 discusses the comparisons among provincial/regional IACI and the related factors. Section 2.5 concludes the study and provides policy recommendations.

2.2. Literature review

As a prerequisite for reducing CO_2 emissions, it is important to determine the factors influencing the changes in CO_2 emissions. In this regard, econometric techniques and decomposition analysis have become popular in recent years. Concerning the former, Xu and Lin (2016a) and Dong et al. (2016) explored the spatial characteristics of industrial emissions and the impacts of socioeconomic factors conducting spatial autocorrelation and regression analysis. Also, using panel data, Wang et al. (2016c) and Xu and Lin (2016b) employed the STIRPAT model to examine, respectively, the driving forces of national and industry's carbon intensity and CO_2 emissions at the regional level. Commonly used decomposition analysis consists of structural decomposition analysis (SDA) and index decomposition analysis (IDA). SDA is often used in combination with input-output analysis, such as Wang et al. (2017a), Su and Ang (2017) and Su et al. (2017). Within IDA (index decomposition analysis) the Laspeyres and Divisia index approaches are the two most often used decomposition methods (Ang and Zhang, 2000). The Laspeyres index approach has the advantage of easily handling the presence of zero values in time series, but nevertheless the decomposition formula becomes very complicated if there are many factors (Ang and Zhang, 2000). Another family of IDA methods, the Divisia index analysis includes the arithmetic mean Divisia index (AMDI) and the LMDI methods. The AMDI has the residual problem and cannot solve the zero-value data problem (Ang, 2004). The LMDI method possesses the advantages of path independency, the ability to handle zero values and consistency in aggregation (Ang, 2004), and has therefore been widely used, such as Brazil (Freitas and Kaneko, 2011), China (Xu et al., 2014a; Zhang and Da, 2015; Xu et al., 2014b), EU (González et al., 2014a, 2014b), and Ireland (Mahony, 2013).

As a large country, China exhibits major heterogeneities in the geographical location of resource endowments, industrial structures and the level of economic development between provinces and regions (Zhou et al., 2017). Hence, in order to promote balanced economic growth China should not only focus on the development of the country as a whole but also pay attention to the local features. IDA has been employed in many recent studies conducted from regional and provincial perspectives in order to formulate sound provincial or regional emission reduction policies. Chen and Yang (2015) decomposed the CO_2 emissions of each province into different factors in eight sub-periods from 1995 to 2011. Xu et al. (2016) and Xu et al. (2017) explored regional contributions to national carbon intensity by decomposing the factors which influence the national carbon intensity. Wang and Feng (2017a) examined the spatial distribution of CO_2 emissions using a gravity model and identified the determinants of CO_2 emissions across provinces to explore possible pathways for China's low-carbon development. Zhang et al. (2016a) extended the LMDI method and investigated the factors (i.e., energy density and energy intensity) influencing the provincial carbon intensity in China. Gao et al. (2016) compared the driving forces of CO_2 emissions in China's east and south coastal regions and identified their provincial features. Li et al. (2016) focused on both carbon emissions per capita and carbon intensity of China's nine typical regions, and then compared their influencing factors. Ding and Li (2017) examined the driving forces and reduction potential of CO_2 emissions in China's different sectors and thirty provinces in the context of rapid urbanization. Jiang et al. (2017) evaluated the contributions of impact factors of 30 provinces to the national carbon emissions combining the two-layer LMDI method with Q-type hierarchical clustering. Yang et al. (2017) analyzed the dynamic CO_2 emissions and the underlying influencing factors at time series. Afterwards the GIS-based approach was employed to verify the previous obtained results from a spatial perspective. Ye et al. (2017) calculated both direct carbon emissions from final energy consumption and the indirect carbon emissions from electricity at the provincial level.

Given that the industrial sector in China is a highly emission-intensive, it has been subject to intensive scrutiny. For instance, Liu et al. (2007) studied the evolution of CO_2 emissions and its influencing factors in each of China's 36 industrial subsectors. Wang et al. (2012) regarded the energy-intensive sectors as a whole and analyzed its changes in CO_2 emissions comprehensively. Xu et al. (2014c) examined the changes in GHG emissions of China's major economic sectors and pointed out that industrial sector played an extremely important role in China. These three studies used the LMDI method and consistently observed that economic activity was the major contributor to the increase in industrial CO_2 (GHG) emissions, whereas the reduction in energy intensity greatly inhibited the expansion of CO_2 (GHG) emissions. Over the past few decades, the energy intensity of China's industrial sector has been continuously decreasing (Xu et al., 2014c), which indicates that energy efficiency has been improving and inevitably led to lower carbon emissions. Yan and Fang (2015), Wang et al. (2016a) and Zhang et al. (2017) integrated the LMDI method and scenario analysis to examine the industrial CO_2 emissions and carbon intensity from historical and future perspectives. Combining the LMDI method and attribution analysis, Liu et al. (2015) and Wang et al. (2017b) respectively identified the factors influencing carbon intensity of China's industrial sector and energy-intensive industries, as well as the contribution of each subsector to the aggregate carbon intensity. Moreover, some typical sub-sectors that play important roles in China's industrial sector have also been studied separately by using the LMDI method, such as the cement industry (Wang et al., 2013), the textile industry (Lin and Moubarak, 2013), the mining sector (Shao et al., 2016) and the chemical industry (Lin and Long, 2014). These studies were all based on time-series data, whereas other studies had a regional focus. Ren et al. (2012) analyzed the regional differences of industrial CO_2 emissions as well as the relevant influencing factors also using the LMDI method. Zhou et al. (2017) first investigated the decoupling between industrial carbon emissions and economic growth of China's eight major regions and then explored the factors influencing carbon emissions using the LMDI method, finding that there were large differences between these regions. Wang and Feng (2017b) combined the LMDI method and production-theoretical decomposition analysis (PDA) to explore the key factors driving the CO_2 emissions of industrial sector at the national, regional and provincial levels. Wang et al. (2018) also used the IDA and PDA to study the factors influencing industrial carbon intensity, and identified the contributions of different provinces to each driving factor based on attribution analysis.

The contribution of previous research work is summarized in Table A1 (provincial/regional level) and Table A2 (sector level). There are still some gaps in the current literature, in particular concerning a detailed discussion of the mechanisms driving the emissions of China's industrial sector in various provinces and their policy implications for provincially-targeted emission mitigation.

This study offers two contributions to the present literature. The first is to employ the ST-LMDI method (Ang et al., 2016) to suggest emission mitigation policies that fit provincial and regional characteristics while taking into account regional disparities, allowing for a comparison between all provinces against a common benchmark. As far as we are aware an ST-LMDI analysis of carbon emissions of the industrial sector across all provinces in China in the period 1999-2015 has never been performed. This type of analysis is important because China has a vast territory with significant regional differences in natural resource endowments and level of industrialization and economic development, and thus the factors driving CO_2 emissions are likely to differ across regions. Several studies referenced above (Ren et al., 2012; Zhou et al., 2017; Wang and Feng, 2017b; Wang et al., 2018) studied the mechanisms driving aggregate emissions in industrial sector by decomposing the industrial aggregate carbon emissions (intensity) from both spatial and temporal perspectives. However, those comparisons from a spatial perspective were not effective enough because the changes in carbon emissions (intensity) were calculated on the basis of carbon emissions (intensity) in the observed year and previous year in each region and lacked a common regional reference benchmark. By contrast, the ST-LMDI method proposed by Ang et al. (2016) uses the same benchmark for spatial comparison in different time periods, which allows the spatial comparisons and temporal changes of an index (e.g., carbon intensity) to be captured simultaneously.

The second contribution of this paper to the literature concerns the study of how the presence of neighbors with different (or the same) level of economic development (and its evolution) affects the IACI. More specifically, this study explores the driving factors of IACI among provinces with same (different) economic development in the context of industrial relocation; and uses spatial autocorrelation (Rey, 2001), the integration of geographical weights with other dominant indicators, to provide additional insights into the location-specific nature of spatial dependence. As far as we are aware, spatial autocorrelation has never been associated with decomposition analysis before. This contribution of the present work is motivated by the observation that in recent years there has been significant industrial relocation among provinces (an industrial enterprise moving from one province to another), especially among adjacent ones, for example, within central and western China as well as from Beijing to Tianjin and Hebei with the guidance of Beijing-Tianjin-Hebei Coordinated Development Plan (Coordinated Development for the Beijing-Tianjin-Hebei Region, 2015). Does industrial relocation promote or inhibit IACI growth between adjacent provinces? Previous studies have answered these questions from several perspectives. Chen et al. (2017) and Chen et al. (2018) pointed out that the industrial relocation was effective for IACI reduction, and it was also useful for national energy efficiency improvement (Liu et al., 2017a; Han et al., 2014). Agglomeration can significantly promote carbon emissions reduction in local and neighboring cities (Han et al., 2018). Lu and Feng (2014) found that the agglomeration of economic activities reduced pollution emission intensity significantly. Related previous researches with a subnational focus but with a lower level of resolution from that of the present paper (30 provinces) was performed by Zhou et al. (2017), Wang and Feng (2017b) (focus on geographical location),Wang and Zhao (2015) (economic performance) or Jiang et al. (2017) (Q-type clustering), which all employed a small number of macro-regions. We believe that considering the resource endowment of each province, as well as the characteristics of the surrounding provinces might improve the understanding of IACI.

2.3. Methodology

2.3.1 Spatiotemporal decomposition analysis

In this paper, the IACI in province *i* in year *t* (CI_i^t) is decomposed into three driving factors based on the following identity:

$$CI_i^t = \frac{C_i^t}{Y_i^t} = \frac{\sum_j C_{ij}^t}{Y_i^t} = \sum_j \frac{C_{ij}^t}{E_{ij}^t} \times \frac{E_{ij}^t}{E_i^t} \times \frac{E_i^t}{Y_i^t} = \sum_j EC_{ij}^t \times EM_{ij}^t \times EI_i^t \tag{1}$$

where the interpretation of each item is as follows. Superscript *t* denotes year and subscript *i* and *j* denote, respectively, the province and fuel type. CI_i^t is the industrial aggregate carbon intensity (IACI) in province *i* in year *t*, measured in million tons CO_2 (Mt)/billion yuan; C_i^t are the industrial CO_2 emissions of province *i* in year *t*, with units of $MtCO_2$/yr; Y_i^t is the industrial value added (IVA) in province *i* in year *t* (unit: billion yuan/yr); C_{ij}^t are the CO_2 emissions from a given fuel type *j* in province *i* in year *t*, with units of $MtCO_2$/yr; E_{ij}^t is the energy consumption of a given fuel type *j* in province *i* in year *t*, measured in Mtce/yr (million tons coal equivalent); E_i^t is the total energy consumption in province *i* in year *t* (Mtce/yr); EC_{ij}^t is the emission coefficient of fuel type *j* in province *i* in year *t* (Mt/Mtce); EM_{ij}^t is the share of fuel type *j* in total energy consumption in province *i* in year *t* (Mtce/Mtce); and EI_i^t is the energy intensity of province *i* in year *t* (Mtce/billion yuan). CO_2 emissions C_i^t and C_{ij}^t are calculated as reported in Appendix B, while the source data of E_{ij}^t, E_i^t and Y_i^t is described in section 2.3.3. Energy types (*j*) in this paper include fossil fuels, electricity and heat, more details in section 2.3.3. All other quantities described in Eq. (1) are derived from these. Note that the CO_2 emissions, various types of energy consumption and IVA all refer to the industrial sector in province *i*.

In the traditional LMDI method, the IACI of region *i* in year *t* is always compared with the IACI in the same region in previous years. In contrast with this traditional method, when employing a spatiotemporal LMDI model a benchmark (reference) province and year are selected and a comparison is made between the IACI of every region and every year with that of the reference province. In this study, the reference province is constructed as exhibiting the arithmetic average indicators values across all provinces in 1999. The IACI of the reference province is measured by the average CO_2 emissions divided by the average IVA of all provinces. The comparison of the IACI between province *i* in year *t* and the reference province is expressed as A^t_i and decomposed as follows:

$$A_i^t = \frac{CI_i^t}{CI_{hp}} = EC_{i,effect}^t \times EM_{i,effect}^t \times EI_{i,effect}^t \tag{2}$$

where CI_{hp} means the IACI of the reference province. $EC_{i,effect}^t$, $EM_{i,effect}^t$, and $EI_{i,effect}^t$ are, respectively, the emission coefficient effect, energy mix effect and energy intensity effect for province i in year t. These terms are all dimensionless and in combination they describe the relation between the IACI of province i in year t and that of the reference province in 1999. These three effects can be calculated based on the multiplicative LMDI-I method[2], whose formulas are listed in Table C1.

The temporal decomposition of IACI in region *i* from year 0 to year *t* can be obtained as:

$$\frac{A_i^t}{A_i^0} = \frac{CI_i^t}{CI_{hp}} / \frac{CI_i^0}{CI_{hp}} = EC_{i,effect}^{0,t} \times EM_{i,effect}^{0,t} \times EI_{i,effect}^{0,t} \tag{3}$$

$EC_{i,effect}^{0,t}$, $EM_{i,effect}^{0,t}$ and $EI_{i,effect}^{0,t}$ are calculated based on the equations in Table C1.

2.3.2 Spatial autocorrelation

Spatial autocorrelation is one of the basic properties used to measure geographic data: the interdependence of data at one location with that of other locations (Wang et al., 2016b; Li et al., 2017b). One of the most commonly used measures is Moran's I index. The global Moran's I index is calculated as follows:

$$I = \frac{n}{\sum_i \sum_p sw_{ip}} \times \frac{\sum_i \sum_p sw_{ip}(x_i - \bar{x})(x_p - \bar{x})}{\sum_p (x_p - \bar{x})^2} \tag{4}$$

where x_i and x_p refer respectively to the per capita GDP of provinces i and p; n is the number of provinces; and sw_{ip} represents the spatial weight matrix, describing the spatial adjacency among provinces. $\bar{x}$ is the mean value of per capita GDP among all provinces. If province i is adjacent to province p, sw_{ip} = 1, otherwise, sw_{ip} = 0. The codomain of Moran's I is [-1, 1]. If this value is closer to 1, the spatial correlation is more obvious. Conversely, the closer this value is to -1, the greater the spatial difference is. If this value is equal to 0, per capita GDP appears a random spatial distribution.

A related metric, the local Moran's I index, can be used to test whether the distribution of the attribute values (e. g., CO_2 emissions, energy consumption and economic development level) between different provinces is clustered or follows a random distribution. Additionally, the local Moran's I can provide more detailed insights into the structure of spatial clustering of the attribute values. Previously, the local Moran's I index has been employed to explore the spatial patterns of carbon emissions (Wang et al., 2016b; Li et al., 2017b). In this paper, the local Moran's I is used to characterize the detailed

[2] The LMDI method consists of additive and multiplicative decomposition forms. When an intensity index is considered, such as carbon intensity, as studied in this paper, the multiplicative LMDI is preferred. The multiplicative LMDI has been further classified into two different sub-methods according to the weights formula used, LMDI-I and LMDI-II, even though the results obtained yield similar results (Ang, 2015).

structure of spatial clustering with regard to per capita GDP. The local Moran's I index is calculated as follows:

$$I_i = \frac{n^2}{\sum_i \sum_p sw_{ip}} \times \frac{(x_i - \bar{x}) \sum_p sw_{ip}(x_p - \bar{x})}{\sum_p (x_p - \bar{x})^2} \tag{5}$$

where I_i is the Moran's I index of province i; $(x_i - \bar{x})$ is the observation variable, measured by difference between the per capita GDP of observation province *i* and the mean of per capita GDP in all provinces; $\sum_p sw_{ip}\,(x_p - \bar{x})$ is the spatial lag, measured by the weighted average of neighbors' observation variable around province i. According to the values of standardized statistics of observation variable and spatial lag, each province could be put into a quadrant, which is the Moran's scatter plot (see Fig.5).

2.3.3 Data sources

This paper is based on the historical data of four specific years, 1999, 2005, 2010 and 2015. Note that 2005, 2010 and 2015 are the termination years of China's Tenth, Eleventh and Twelfth five-year plan (FYP), so this paper can identify how the IACI changed and what were its driving factors during each FYP period. 1999 is chosen as the initial year because energy balances of Ningxia in 2000 and 2001 are not available. The CO_2 emissions were calculated on the basis of final energy consumption. Nineteen types of energy were considered: raw coal, cleaned coal, washed oil, coke, coke oven gas, briquettes, other gas, other coking products, crude oil, gasoline, kerosene, diesel oil, fuel oil, LPG, refinery gas, natural gas, other petroleum, heat, and electricity. The energy consumption data were collected from the China Energy Statistic Yearbook (NBSC, 2000-2016a). The IVA data were collected from the China Statistic Yearbook (NBSC, 2000-2016b). The double deflation method (Liu et al., 2015) is used to convert the raw data of IVA to 1999 constant price through the regional industrial producer price indexes (NBSC, 2000-2016b).

2.4. Results and discussion

Using the spatiotemporal LMDI-I method, a comprehensive description of variations in IACI of China's thirty provinces is obtained, allowing for a comparison of IACI change in each province with respect to the national average level in 1999. The results also allow the ranking of provinces by IACI, and the identification of how energy intensity, energy structure and emission coefficients affect IACI over time in each province. This section first presents the spatial and temporal decomposition results at provincial level and afterwards the spatial cluster and regional decomposition results.

2.4.1 Provincial comparisons

2.4.1.1 Spatial comparisons between provinces

The changes in the IACI of each province against the reference province in four specific years are illustrated in Fig.1. The effects of energy intensity, energy structure and emission coefficient on provincial IACI are presented in Fig. 2, which are obtained by comparing each province with the reference one.

As shown in Fig.1, a value over (under) 1 implies that the IACI of a particular province was greater (lower) than that of the reference province. In 1999, nineteen provinces performed worse than the national average level. Among them, the IACI of Shanxi was approximately 240% higher than that of the reference province. The IACI of Inner Mongolia, Ningxia, Guizhou and Chongqing was also more than 100% higher than the reference province. The performances of Anhui, Qinghai, Gansu, Guangxi, Jiangxi, Hebei, Liaoning, Jilin, Xinjiang, Hunan, Sichuan, Shaanxi, Henan and Hubei were worse than the reference province, but their IACI was less than 100% above the reference value. The remaining provinces performed better than the reference province, especially Guangdong, whose IACI was 55.21% lower than the average level. From Fig. 1, it can be seen that the number of provinces on the right side of the y-axis decreased continuously from nineteen in 1999 to five in 2015. The performances of Hubei, Sichuan and Shaanxi in 2005, as measured by IACI, became better than that of the reference province. There were eleven additional provinces including Liaoning, Jilin, Anhui, Jiangxi, Henan, Hunan, Guangxi, Chongqing, Qinghai, Guizhou and Gansu, whose IACI dropped below that of the reference province in 2010 and 2015. The IACI in each province was jointly determined by the effects of energy intensity, energy structure and emission coefficient. As shown in Fig. 2, energy intensity had an inhibitory effect in the growth of IACI over time in most provinces, e.g., Shaanxi, Hubei, Sichuan, Henan and Jiangxi in 2005, Jilin, Anhui, Liaoning, Chongqing, Yunnan, Guangxi and Hunan in 2010 and Guizhou, Inner Mongolia and Gansu in 2015. Regarding energy intensity improvements, Shanghai, Beijing and Guangdong can be considered as benchmarks. The energy intensity of Ningxia, Shanxi and Hebei was worse than the average level. In contrast to energy intensity, the performance of energy structure decreased in some provinces: Xinjiang, Anhui, Liaoning, Chongqing, Inner Mongolia, Hebei, Hubei, Jiangsu and Guangdong. These nine provinces performed better than the reference province in terms of energy structure in 1999 while worse in 2015. In contrast, the performance of the energy structure of Beijing, Tianjin, Hainan and Sichuan improved during the study period. Comparatively speaking, Heilongjiang had the best performance in energy structure, while the energy structure of Ningxia was the worst. In 1999 only seventeen provinces performed better in terms of the emission coefficient than the reference province, while in 2015 this number has grown to twenty-five. The regions that became above-average performers in 2015 but were below-performers in 1999 were Shanxi, Jiangsu, Jiangxi, Shandong, Henan, Shaanxi, Xinjiang, Hebei and Anhui. Concerning the performance of emission coefficients, during the whole study period Qinghai, Hubei, Yunnan and Sichuan ranked the top four performers and Heilongjiang, Inner Mongolia and Jilin performed the worst.

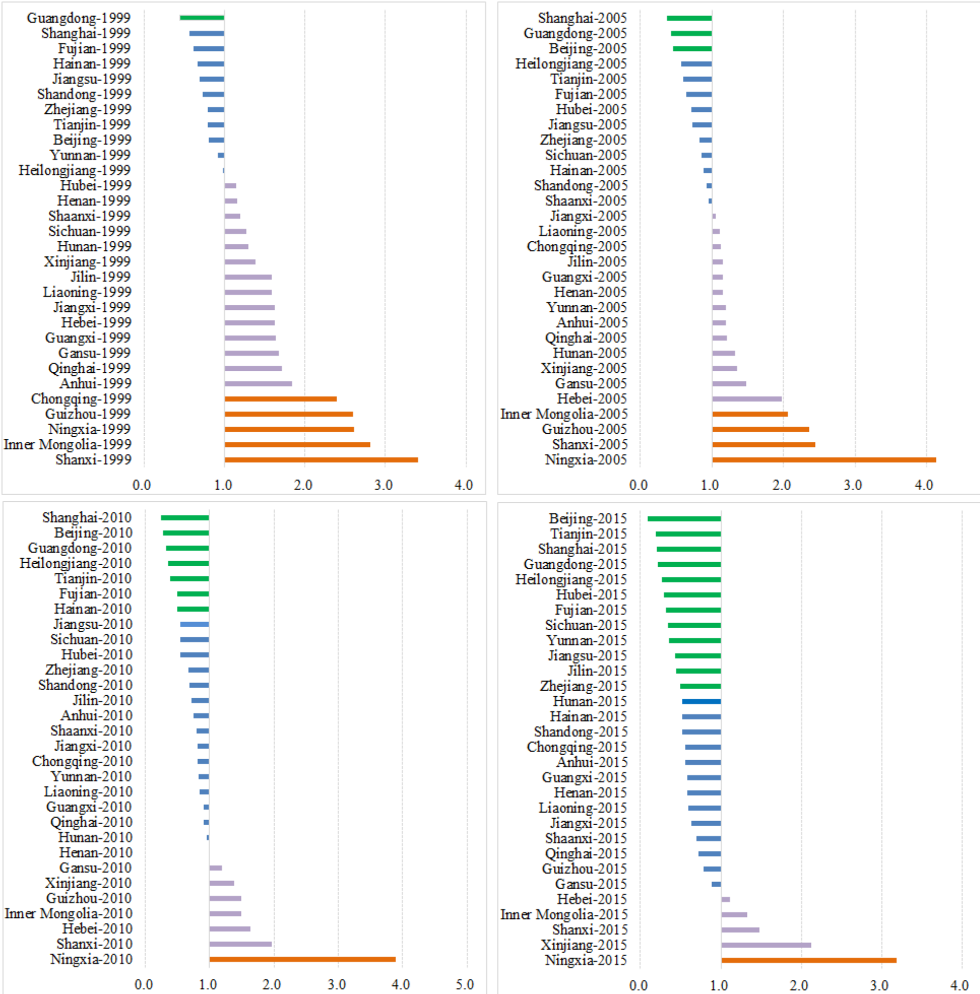

Fig.1. Rankings of China's 30 provincial IACI in 1999, 2005, 2010 and 2015 relative to the reference province. The results are given in adimensional ratios. Green bars indicate that the ratios are lower than 0.5; blue bars indicate that the ratios are between 0.5 and 1; purple bars indicate that the ratios are between 1 and 2; and orange bars indicate that the ratios are larger than 2.

As shown in Fig. 1, there were five provinces whose IACI was higher than the reference province during the whole study period: Hebei, Shanxi, Inner Mongolia, Ningxia and Xinjiang. These five provinces are located in central and western China, and their industrial development modes rely on extensive energy consumption. An analysis of the factors influencing the changes in IACI of these five provinces (see Fig. 2) shows that the evolution of energy intensity had the effect of increasing IACI in Hebei, Shanxi, Ningxia and Xinjiang from 1999 to 2015 and in Inner Mongolia from 1999 to 2010. The factor of energy structure contributed to increase IACI of Shanxi and Ningxia during the whole study period, while its impact on Hebei, Inner Mongolia and Xinjiang changed over time. The

IACI of Shanxi and Inner Mongolia decreased over the whole study period, while the other three provinces exhibited erratic fluctuations. Ten provinces performed better than the reference province during the whole study period in terms of IACI, of which Beijing, Tianjin, Shanghai, Guangdong and Heilongjiang ranked as the top five provinces (Table C2). The main reason for the lower IACI than the reference province for these provinces is that energy intensity had a substantial effect on decreasing IACI, a pattern which was reinforced by the emission coefficient factor in most provinces. Even though energy structure contributed to increase the IACI in all provinces except Heilongjiang, it was not large enough to offset the reducing effect of other factors. Remaining provinces had higher IACI in the initial years and lower in the later years, indicating an improvement in their performance from 1999 to 2015. It should be noted that the IACI performance of several provinces was worse in 2005 than that of 1999 (e.g., Hebei, Jiangsu and Zhejiang), which was mainly caused by the energy intensity and energy structure factors. This phenomenon may be linked to the entrance to the World Trade Organization (WTO) in 2001. After that, the exports of industrial products to the global countries increased rapidly, which directly led to an increase in industrial production and energy consumption.

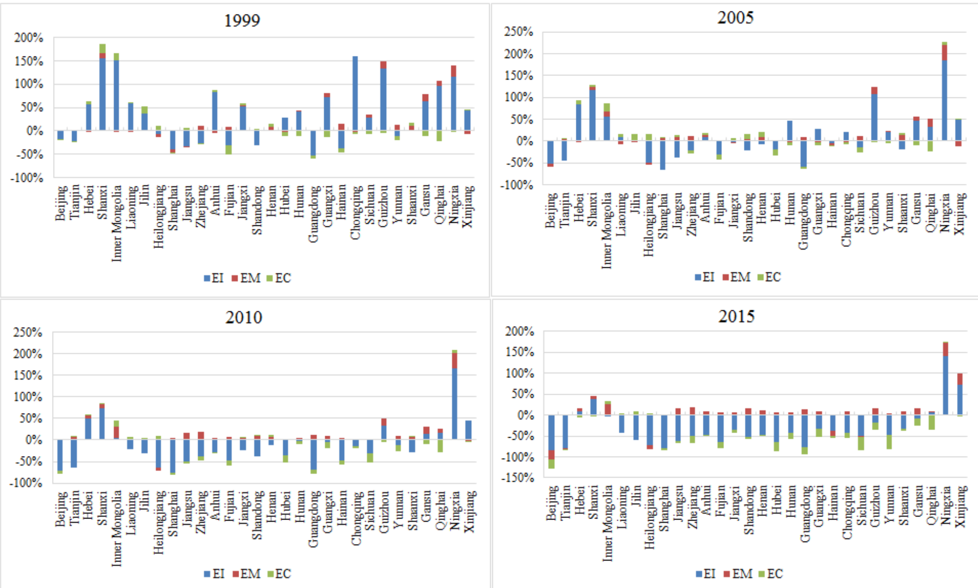

Fig.2. Spatial decomposition results in 1999, 2005, 2010 and 2015 (the contributions of EI, EM and EC to the changes in IACI are given in ratios). EI, EM and EC mean the energy intensity effect, energy mix effect and emission coefficient effect, respectively.

2.4.1.2 Temporal changes in IACI

Fig. 3 describes in a comprehensive way the variations in IACI from a temporal perspective for thirty provinces. The IACI decreased during the examined period of 1999-2015 in each province except Ningxia and Xinjiang. This evolution may be a reflection of the success of the energy conservation and emissions mitigation policies and measures implemented during that period. The thirty provinces can be divided into four categories, according to their temporal changes in IACI. The IACI of Beijing, Tianjin, Jilin, Chongqing, Heilongjiang, Hubei and Sichuan decreased more than 70%. Shanxi, Inner Mongolia, Liaoning, Shanghai, Anhui, Jiangxi, Hunan, Guangdong, Guangxi, Guizhou, Yunnan and Qinghai were the following provinces in terms of IACI performance, and the values of their IACI decreased between 50% and 70%. The performance of Ningxia and Xinjiang did not experience progress, especially for Xinjiang whose IACI increased by 53.14% from 1999 to 2015. The IACI in the remaining provinces decreased by a value of less than 50%.

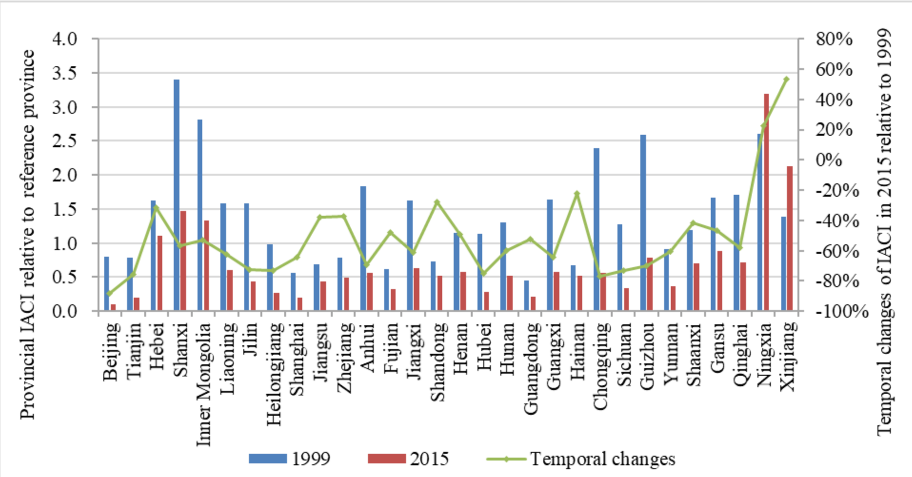

Fig.3. Provincial IACI relative to reference province in 1999 (blue bars) and in 2015 (red bars) as adimensional ratios (left axis) and the change in provincial IACI from 1999 to 2015 (green line) in % (right axis).

As shown in Table 1, the energy intensity factor had a dramatic impact on the reduction of IACI in all provinces except Ningxia and Xinjiang, with a contribution of more than 50% in most provinces. On the contrary, the energy intensity factor was the strongest contributor to the increase of IACI in Xinjiang. The economic growth of Xinjiang has been strongly driven by source-extensive exports.

Table 1. Temporal decomposition results of IACI of the industrial sector in China's thirty provinces from 1999 to 2015. The item "IACI" in this table is the IACI of different provinces in 2015 relative to their IACI in 1999 in ratios. EI, EM and EC are the energy intensity effect, energy mix effect and emission coefficient effect (adimensional), respectively.

Province	IACI	EI	EM	EC	Province	IACI	EI	EM	EC
Beijing	0.1189	0.1866	0.7858	0.8110	Henan	0.5050	0.5141	1.0456	0.9395
Tianjin	0.2465	0.2632	0.9566	0.9792	Hubei	0.2529	0.2717	1.0755	0.8654
Hebei	0.6816	0.6942	1.0854	0.9047	Hunan	0.3988	0.4050	1.0286	0.9572
Shanxi	0.4328	0.5419	0.9677	0.8252	Guangdong	0.4777	0.4638	1.1444	0.9000
Inner Mongolia	0.4714	0.3906	1.2797	0.9430	Guangxi	0.3543	0.3905	0.9875	0.9188
Liaoning	0.3765	0.3684	1.0446	0.9784	Hainan	0.7772	0.9961	0.7485	1.0425
Jilin	0.2778	0.2926	1.0184	0.9325	Chongqing	0.2327	0.2246	1.1150	0.9291
Heilongjiang	0.2668	0.2980	0.9688	0.9240	Sichuan	0.2668	0.3908	0.9080	0.7519
Shanghai	0.3538	0.3503	1.0633	0.9500	Guizhou	0.3018	0.3492	1.0073	0.8579

Jiangsu	0.6213	0.5860	1.1822	0.8970	Yunnan	0.3918	0.5762	0.9310	0.7303
Zhejiang	0.6279	0.6674	1.0806	0.8706	Shaanxi	0.5862	0.6766	0.9925	0.8730
Anhui	0.3057	0.2907	1.1155	0.9425	Gansu	0.5323	0.5531	1.0151	0.9481
Fujian	0.5200	0.5210	0.9695	1.0294	Qinghai	0.4184	0.5472	0.9088	0.8412
Jiangxi	0.3913	0.4206	1.0461	0.8893	Ningxia	1.2239	1.1187	1.0562	1.0358
Shandong	0.7215	0.6717	1.1216	0.9577	Xinjiang	1.5314	1.1959	1.3732	0.9325

From 1999 to 2015, the influence of the energy structure factor on IACI varied significantly across provinces. Energy structure had no significant impact on the reduction in IACI in Shaanxi (contribution lower than 1%). In five provinces, such as Tianjin, Shanxi, Heilongjiang, Fujian and Guangdxi the energy structure factor had an impact on reducing IACI between 1% and 5%. Next in order, energy structure contributed to reduce IACI of Sichuan, Qinghai and Yunnan by 9.2, 9.12 and 6.90%, respectively. The energy structure factor had a significant impact on the reduction of IACI of Beijing and Hainan, with values of 22.42 and 25.15%, respectively. However, in the remaining provinces, the energy structure factor contributed to increase their IACI, especially for Inner Mongolia and Xinjiang with values of 27.97% and 37.32%. In addition, the energy structure contributed to the increase of IACI in Jiangsu, Anhui, Shandong, Guangdong and Chongqing by more than 10%. The energy structure effect expresses a change in the proportion of different energy sources that constitute total energy consumption. According to the data set of energy use, the consumption of low-carbon energy types expanded in the provinces in which energy structure contributed to a decrease in IACI. For instance, the coal-related energy share of most of these provinces decreased significantly while natural gas increased to different extents, especially for Hainan and Beijing. In addition, there were some provinces whose coal- and oil-related energy consumption decreased, while energy structure contributed to increase IACI (e.g., Inner Mongolia): in these provinces, the proportion of electricity consumption rose substantially and the emission factors of electricity in these provinces were larger than other provinces (see Fig. 4).

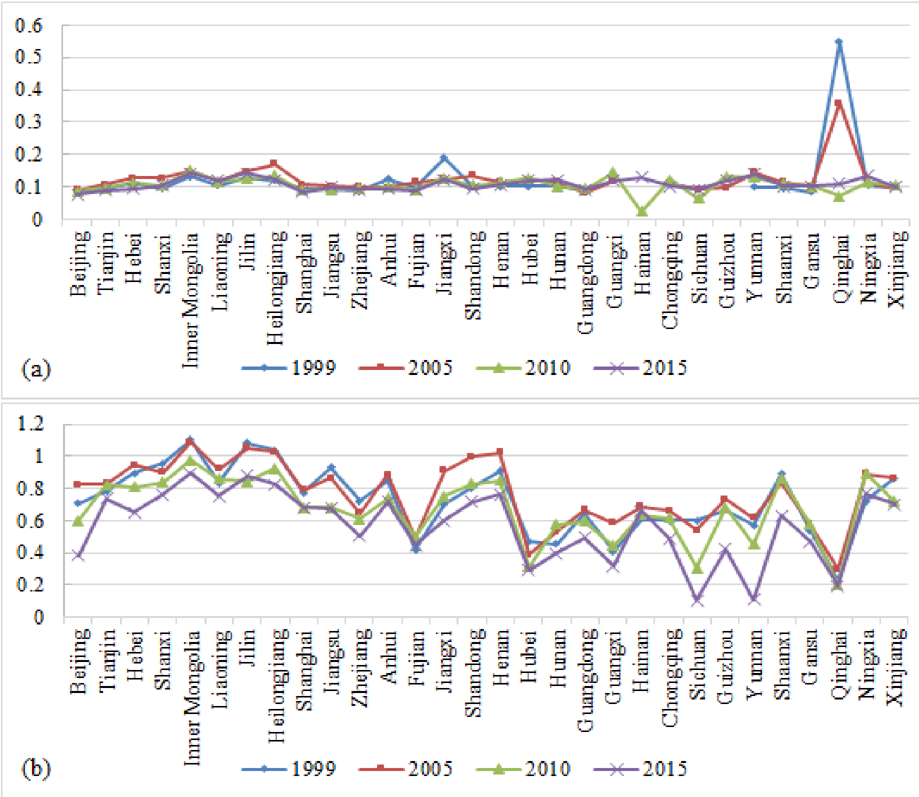

Fig.4. Average carbon emission coefficients of China's 30 provinces from 1999 to 2015. (a) Heat generation (unit: Kg/MJ) and (b) electricity generation (Kg/KWh).

In this paper, the emission coefficient effect is determined by changes in the emission coefficients of electricity and heat since the emission coefficients of fossil fuels are considered to be constant throughout the time series. The emission coefficient effect remained positive for Fujian (+2.94%), Hainan (+4.25%) and Ningxia (+3.58%). Fig. 4 shows that the emission coefficients of electricity in Fujian, Hainan and Ningxia increased from 1999 to 2015. Additionally, although the coefficient of heat in Fujian improved, the increase in the coefficient of electricity was greater. In contrast, the emission coefficient factor contributed to decrease IACI in other provinces. In particular, the emission coefficient factor contributed to a decrease in IACI of Sichuan and Yunnan by 24.81 and 26.97%, respectively. This evolution can be attributed to the vigorous promotion of hydroelectric power generation in these two provinces, which resulted in a large reduction of electricity emissions' coefficient. More importantly, with the promotion of photovoltaic, wind and biomass power generation, there has been significant improvement in the coefficients of electricity in most provinces.

2.4.2 Regional comparisons of decomposition results

The global Moran's I index of China's province-level per capita GDP is 0.208043. The *Z* score and *P* value are respectively 3.10 and 0.0020, which implies that the Moran's I index passes the significance test at the 1% level and indicates that there is significant spatial autocorrelation in China's province-level per capita GDP. Thus, provinces with a high (or low) GDP per capita value often have neighboring provinces with a high (or low) value. This spatial relationship among adjacent provinces can be visualized by Moran's I scatter plot analysis (Wang et al., 2016b; Zhang et al., 2016b).

The Moran's I scatter plot of per capita GDP in Chinese provinces is shown in the right section of Fig. 5. The horizontal axis of the scatter plot represents the standardized statistics of observation variable while the vertical axis represents the standardized statistics of corresponding spatial lag. There is a straight line in Moran's I scatter plot, which is the result of linear regression between spatial lags and observation variables. The slope coefficient of this straight line is the global Moran's I index, 0.208043. There are four quadrants in this figure, indicating that the thirty provinces are divided into four clusters. If a province and its neighbors all have per capita GDP values above average, it will in the first quadrant. The provinces in the first quadrant form is the high-high cluster (HH). The second quadrant is the low-high cluster (LH), which is characterized by provinces with low values (per capita GDP below average) being surrounded by provinces with high values. Similarly, the group comprised by provinces in the third quadrant is the low-low cluster (LL) and the fourth quadrant is the high-low cluster (HL). The left section of Fig. 5 shows the spatial distribution of the four provincial clusters, as defined by the scatter plot.

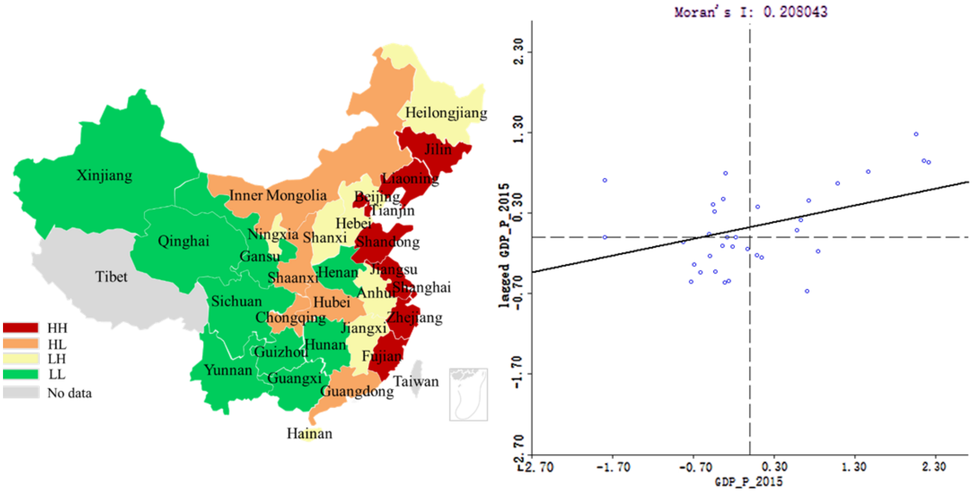

Fig.5. Spatial patterns and Moran scatter plot of per capita GDP in 2015.

The decomposition results of regional IACI are shown in Fig. 6. Examining the IACI in the left of *y*-axis it is possible to see that the HH and HL clusters performed better than the LH and LL clusters, during the whole study period. More specifically, the HH cluster has the lowest IACI in 1999 with a value of 79.28%, while the IACI of HL cluster was the lowest (and below that of the reference region) in 2005, 2010 and 2015 with values of 35.36, 48.08 and 58.91%, respectively. Even though the IACI of the LL cluster was higher than the reference region by 21.12 and 15.96% in 1999 and 2005, respectively, continuous improvements took place leading to IACI becoming 12.29 and 38.74% lower than the reference region in 2010 and 2015, respectively. The worst performance occurred in the LH cluster, whose IACI was higher than the reference region over the whole study period. These results can be attributed to the interaction between the energy intensity, energy structure and emission coefficient effects shown in Table 2. For HH and HL clusters, improvements in energy intensity contributed strongly to decrease IACI during the whole study period. The energy intensity factor contributed to increase IACI of the LH cluster by 54.12, 33.66, 2.04, and 25.98% in 1999, 2005, 2010 and 2015, respectively. Energy intensity contributed to increase IACI of the LL cluster by 25.44 and 15.22% in 1999 and 2005, respectively. On the whole, energy structure always contributed to drive up IACI with the exception of the year 1999 for the HL and LH clusters. The emission coefficient factor had a small impact on IACI, whether positive or negative. In the period under examination, the emission coefficient factor contributed to a reduction of IACI of the HL and LL clusters while it contributed to an increase for LH. In the HH cluster, the emission coefficient factor had mixed effects on IACI. Between 1999 and 2005 it contributed to an increase while in 2010 and 2015 it contributed to a decrease. From time series perspective, HH, HL, LH and LL showed continuous improvement in IACI, driven by improvements in energy intensity and emission coefficient. On the contrary, changes in the energy structure did not contribute to reduce IACI in any region.

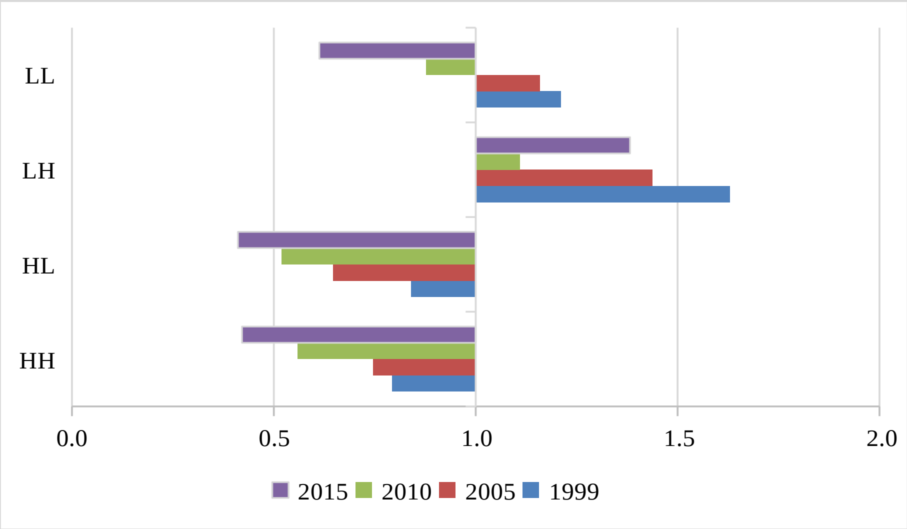

Fig.6. The IACI of each of the four clusters relative to the reference province in 1999, 2005, 2010 and 2015 (adimensional ratio).

Table 2. Decomposition results of IACI for each of the four clusters in 1999, 2005, 2010 and 2015, relative to the reference province (adimensional ratios). EI, EM and EC mean the energy intensity, energy mix and emission coefficient, respectively.

Clusters	EI effect				EM effect				EC effect			
	1999	2005	2010	2015	1999	2005	2010	2015	1999	2005	2010	2015
HH	0.786	0.689	0.521	0.390	1.000	1.044	1.100	1.109	1.009	1.037	0.975	0.975
HL	0.886	0.619	0.496	0.383	0.978	1.070	1.096	1.125	0.969	0.976	0.956	0.955
LH	1.541	1.337	1.020	1.260	0.995	1.014	1.072	1.082	1.063	1.061	1.014	1.014
LL	1.254	1.152	0.903	0.614	1.022	1.027	1.056	1.084	0.945	0.980	0.919	0.920

From the results above, it can be seen that developed provinces (per capita GDP above average) with less-developed (per capita GDP below average) neighbors performed best in terms of IACI while the LH cluster performed the worst during the whole study period. This result can be explained by a phenomenon that developed areas tended to transfer their energy-intensive industries to less-developed areas. For instance, Hebei is a less-developed province surrounded by Beijing and Tianjin, which are developed provinces. Over the past few years, energy-intensive industrial sectors transferred from Beijing to Hebei, which resulted in the rapid increase in industrial CO_2 emissions of Hebei. In this case, perhaps the developed area should take the initiative to promote technological innovation and investment in the less developed one. The HH cluster had higher IACI than the HL group even though the differences were not significant. Fig.6 shows that the east-coast areas are all included in HH cluster. From 2004 onward, energy-intensive industries in these areas shifted to less-developed area, and the economic development of the HH cluster can be attributed mainly to the expansion of the service sector and high-tech industries (NBSC, 2016b). Hence, economic development within the HH cluster had the net effect of decreasing carbon emissions. In order to promote local employment and GDP, less developed areas tend to allow the introduction of emission-intensive industries without major constraints. This pattern results in carbon mitigation in developed areas and carbon emission increase in less-developed areas.

2.4.3. Discussion

Even though Wang and Feng (2017b) and Zhou et al. (2017) deal with industrial CO_2 emissions from a perspective which differs from that of the present study, it is perhaps interesting to compare their results. Wang and Feng (2017b) observed that from 2000 to 2015 the CO_2 emissions of most provinces increased except for Beijing. Energy intensity led to the reduction in industrial CO_2 emissions in twenty-two provinces and was the most important factor driving down emissions. In addition, changes in the energy structure brought about reductions in thirteen provinces. In contrast to Wang and Feng (2017b), Zhou et al. (2017) focused on the industrial CO_2 emissions of China’s eight regions. Their results showed that the lowest growth rate of industrial CO_2 emissions was that of the Beijing-Tianjin region. The energy intensity factor had the strongest contribution in the reduction of the carbon emissions’ growth rate. After 2006, shifts in the energy structure gradually contributed to reduce carbon emissions in most regions. However, shifts in the energy structure still contributed to increase carbon emissions in the northeast region. In our study, the IACI decreased from 1999 to 2015 in most provinces (all except Ningxia and Xinjiang), with energy intensity playing the decisive role. Changes in energy structure contributed to decrease IACI of twelve provinces, while changes in emission coefficients caused a reduction in IACI of most provinces (all except Fujian, Hainan and Ningxia). The results of these three studies are consistent to some degree. The discrepancies are mainly due to differences in the method, the factors being decomposed and the study period. Additionally, our study ranked the performance of IACI as well as its influencing factors in all provinces against a common benchmark, revealing that Beijing, Tianjin, Shanghai, Guangzhou and Heilongjiang ranked as the top five provinces while Ningxia, Shanxi, Inner Mongolia and Xinjiang performed relatively poor. These results were not apparent in previous studies because there the change in CO_2 emissions was calculated separately for each province, lacking a common benchmark. From the comparisons above, it can be seen that Beijing can be regarded as the top performer both in CO_2 emissions and carbon intensity, while Xinjiang and Ningxia should increase efforts to reduce their CO_2 emissions and carbon intensity by developing the energy conservation technology and adjusting their energy structure. This study indirectly assessed the effect of industrial relocation between adjacent provinces on IACI and related driving factors, indicating that the IACI of all regions decreased over time. These results are partially consistent with Chen et al. (2017), Chen et al. (2018) and Lu and Feng (2014).

Since the main objective of spatial IDA is to study regional disparities, it often makes sense to compare each region with a region that is representative or meaningful. Therefore, when conducting a spatial LMDI study, a reference province (region) which serves as a benchmark for comparisons needs to be first selected. According to Ang et al. (2016), the benchmark can be an existing region or a hypothetical one. In that paper these alternatives are obtained as: (1) choosing a region from the research group, such as the best or the worst one; (2) constructing a region based on the research group, such as the arithmetic (weighted) average of indicators of all the regions studied, or the arithmetic (weighted) average of all the regions in the dataset except the region to be compared. The former can help us to understand the gap between regions and a specific one (the best or worst player) while the latter allows us to define a reference region according to the regions in the research group. The choice of benchmark depends on your specific needs and what you want to address, because it will yield different decomposition results (Ang et al., 2016). In the recent literature, Ang et al. (2015) developed the spatial IDA framework by comparing the energy performance of each country with a reference country which was constructed as the arithmetic average of the indicator values of all countries studied. Using the same method to define the reference region, Liu et al. (2017b) and Li et al. (2017a) explored the regional carbon intensity of China's electricity generation and China's CO_2 emissions at both national and regional level, respectively. In contrast to these studies, Ang and Goh (2016) used the weighted average when constructing the reference region to study the aggregate carbon intensity of electricity production sector in the Association of Southeast Asian Nations. In this study, we want to explore the performance rankings of industrial carbon intensity in different provinces, so a fair comparison base should be preferred and we chose the arithmetic national average as the benchmark. We are also interested in what will happen to the spatial decomposition results if the weighted average is selected. If we perform a similar study in the future, the weighted average will be the preferred choice in the selection of the reference province (region).

2.5. Conclusions and policy implications

Considering the existence of significant discrepancies across provinces, in order to achieve the reduction targets of IACI in China, it is critical to clarify the driving factors of IACI and compare differences at the provincial level and propose differentiated policy recommendations to mitigate carbon emissions. This paper first employed the spatiotemporal LMDI method to study the disparities of provincial IACI in China as well as the cumulative changes in the intensity of each province that took place from 1999 to 2015. Then the local spatial autocorrelation was applied to divide China into four clusters (e. g., HH, HL, LH and LL) and to identify the contributions of related factors to each cluster as well as the differences that existed among them. The results indicate that Beijing, Tianjin, Shanghai, Guangzhou and Heilongjiang performed best, exhibiting a IACI largely below that of the reference province. The IACI of five provinces (e.g., Hebei and Shanxi) was higher than the average level during the whole study period. From the temporal perspective, the IACI declined for most of the provinces except for Ningxia and Xinjiang, with the energy intensity factor playing a crucial role for all provinces. Changes in the energy structure of nine provinces (e.g., Hebei, Inner Mongolia) led to a reduction in IACI from 1999 to 2015. Also, from 1999 to 2015, the emission coefficients of thirteen provinces were below that of the reference province, especially Hubei, Guangxi, Sichuan and Yunnan. Moreover, when taking provincial spatial differences into account, the proposed classification of China's provinces presented in this paper was significantly different from that of previous studies, which relied mainly on geographical positions (Zhou et al., 2017; Wang and Feng, 2017b), economic performance (Wang and Zhao, 2015) or Q-type clustering (Jiang et al., 2017). The results of the decomposition into four clusters show that the IACI of HH and HL was lower than the average level during the whole study period, while LH and LL clusters performed relatively worse. The performances of the four clusters in energy intensity were similar to those of IACI. Energy structure led to a percent increase of IACI for all clusters during the whole study period except for HL and LH in 1999. The emission coefficient had little impact on IACI for all clusters. Based on the results, some feasible policy recommendations are as follows:

First, the policies and measures of energy efficiency improvement should be implemented in the industrial sector of provinces who performed relatively poor in terms of energy intensity. According to the results, energy intensity is a decisive factor in driving carbon intensity, which can be improved through the adoption of energy-saving technology. Therefore, the government should continue to increase the investment on the introduction and development of advanced energy-saving technologies. In addition, given that the energy efficiency of developed provinces has improved to a large extent, the government of less-developed regions should introduce the energy-saving technologies or energy efficient production equipment from their adjacent developed provinces. Due to heterogeneity in energy intensity among provinces, they should take their advantages of nature resources and existing technology levels into consideration when promoting research and development and introducing advanced technology. Finally, coal-dependent provinces, such as Hebei, Shanxi and Inner Mongolia, have a relatively high energy intensity and are also experiencing rapid industrialization and urbanization, suggesting that their energy consumption will continue to increase in the long run. Therefore, the quality and utilization efficiency of coal products should be improved by scientific and technological innovation in the coal industry.

Second, the energy structure for industrial sector in most provinces should be adjusted, especially in Inner Mongolia, Jiangsu and Guangdong. Since most CO_2 emissions in China are caused by the combustion of fossil fuels, the adjustment of the energy structure means that emission-intensive energy sources, such as fuel oil and crude oil, should be replaced by clean energy sources (e.g., natural gas). Inter-provincial energy cooperation can be promoted to develop and utilize the low-carbon fuels.

Third, with the increase of electricity consumption in total energy consumption, it is urgent and effective to encourage non-fossil power generation. Electricity generation from various forms of non-fossil energy has risen significantly over the past decade, especially hydro, wind and photovoltaic power. The increase in the share of non-fossil energy in power generation has been substantial in Qinghai, Yunnan, Sichuan, Guizhou, Huanan, Hubei and Fujian. In 2015 the shares of total electricity generated from non-fossil sources in these provinces are, respectively, 78.45, 89.56, 85.87, 45.79, 46.84, 56.89 and 43.12%, which are much higher than the national level of 25.76%. Considering the advantages of resource endowments, Xinjiang, Inner Mongolia, Qinghai, Shaanxi, Ningxia and Gansu should increase the installed capacity of wind and solar for power generation, while hydro power should be encouraged in Sichuan and Yunnan. Additionally, nuclear power generation should be further promoted in Zhejiang, Shandong, Guangdong and Jiangsu, while biomass power generation should also be promoted in all provinces.

References

Ang, B.W., 2004. Decomposition analysis for policymaking in energy: which is the preferred method? Energy Policy 32 (9), 1131-1139.

Ang, B.W., 2015. LMDI decomposition approach: a guide for implementation. Energy Policy. 86, 233-238.

Ang, B.W., Goh, T., 2016. Carbon intensity of electricity in ASEAN: drivers, performance and outlook. Energy Policy 98, 170-179.

Ang, B.W., Xu, X.Y., Su, B., 2015. Multi-country comparisons of energy performance: the index decomposition analysis approach. Energy Economics 47, 68-76.

Ang, B.W., Su, B., Wang, H., 2016. A spatial-temporal decomposition approach to performance assessment in energy and emissions. Energy Economics 60, 112-121.

Ang, B.W., Zhang, F.Q., 2000. A survey of index decomposition analysis in energy and environmental studies. Energy 25 (12), 1149-1176.

Chen, D.K., Chen, S.Y., Jin, H., 2018. Industrial agglomeration and CO_2 emissions: evidence from 187 Chinese prefecture-level cities over 2005-2013. Journal of Cleaner Production 172, 993-1003.

Chen, L., Xu, L.Y., Yang, Z.F., 2017. Accounting carbon emission changes under regional industrial transfer in an urban agglomeration in China's Pearl River Delta. Journal of Cleaner Production 167, 110-119.

Chen, L., Yang, Z., 2015. A spatio-temporal decomposition analysis of energy-related CO_2, emission growth in China. Journal of Cleaner Production 103, 49-60.

Coordinated Development for the Beijing-Tianjin-Hebei Region, 2015. URL: < http://www.hebqhdsgt.gov.cn/gtzyj/front/6048.htm>.

Ding, Y., Li, F., 2017. Examining the effects of urbanization and industrialization on carbon dioxide emission: evidence from China's provincial regions. Energy 125, 533-542.

Dong, L., Liang, H., Luo, X., Ren, J., 2016. Balancing regional industrial development: analysis on regional disparity of China's industrial emissions and policy implications. Journal of Cleaner Production 126, 223-235.

Freitas, L.C.D., Kaneko, S., 2011. Decomposing the decoupling of CO_2 emissions and economic growth in Brazil. Ecological Economics. 70 (8), 1459-1469.

Gao, C., Liu, Y., Jin, J., Wei, T.Y., Zhang, J.Y., Zhu, L.Z., 2016. Driving forces in energy-related carbon dioxide emissions in east and south coastal China: commonality and variations. Journal of Cleaner Production 135, 240-250.

González, P.F., Landajo, M., Presno, M.J., 2014a. Multilevel LMDI decomposition of changes in aggregate energy consumption. A cross country analysis in the EU-27. Energy Policy 68 (5), 576-584.

González, P.F., Landajo, M., Presno, M.J., 2014b. The driving forces behind changes in CO_2, emission levels in EU-27. Differences between member states. Environmental Science & Policy 38 (3), 11-16.

Han, F., Xie, R., Lu, Y., Fang, J.Y., Liu, Y., 2018. The effects of urban agglomeration economics on carbon emissions: evidence from Chinese cities. The driving forces behind changes in CO_2, emission levels in EU-27. Differences between member states 172, 1096-1110.

Han, F., Feng, P., Yang, L.G., 2014. Spatial agglomeration effects of China's cities and industrial energy efficiency. China Population Resources & Environment 24 (5), 72-79 (In Chinese).

Intergovernmental Panel on Climate Change (IPCC), 2007. Fourth Assessment Report of IPCC. Cambridge University Press, UK.

Jiang, J., Ye, B., Xie, D., Tang, J., 2017. Provincial-level carbon emission drivers and emission reduction strategies in China: combining multi-layer LMDI decomposition with hierarchical clustering. The driving forces behind changes in CO_2, emission levels in EU-27. Differences between member states 169, 178-190.

Li, A., Hu, M., Wang, M., Cao, Y., 2016. Energy consumption and CO_2, emissions in Eastern and Central China: a temporal and a cross-regional decomposition analysis. Technology Forecasting & Social Change 103, 284-297.

Li, H., Zhao, Y.H., Qiao, X.Y., Liu, Ya, Cao, Y., Li, Y., et al., 2017a. Identifying the driving forces of national and regional CO_2 emissions in China: based on temporal and spatial decomposition analysis models. Energy Economics 68, 522-538.

Li, W., Sun, W., Li, G.M., Cui, P.F., Wu, W., Jin, B.H., 2017b. Temporal and spatial heterogeneity of carbon intensity in China's construction industry. Resources, Conservation and Recycling 126, 162-173.

Lin, B.Q., Long, H., 2014. Promoting carbon emissions reduction in China's chemical process industry. Energy 77 (C), 822-830.

Lin, B.Q., Moubarak, M., 2013. Decomposition analysis: change of carbon dioxide emissions in the Chinese textile industry. Renewable & Sustainable Energy Reviews 26 (10), 389-396.

Liu, J., Cheng, Z.H., Zhang, H.M., 2017a. Does industrial agglomeration promote the increase of energy efficiency in China? Renewable & Sustainable Energy Reviews 164, 30-37.

Liu, L.C., Fan, Y., Wu, G., Wei, Y.M., 2007. Using LMDI method to analyze the change of China's industrial CO_2 emissions from final fuel use: an empirical analysis. Energy Policy 35 (11), 5892-5900.

Liu, N., Ma, Z.J., Kang, J.D., 2015. Changes in carbon intensity in China's industrial sector: decomposition and attribution analysis. Energy Policy 87, 28-38.

Liu, N., Ma, Z.J., Kang, J.D., 2017b. A regional analysis of carbon intensities of electricity generation in China. Energy Economics 67, 268-277.

Lu, M., Feng, H., 2014. Agglomeration and reduction: empirical study of industrial pollution intensity on cities. J. World Econ. Chin. 86-144.

Mahony, T.O., 2013. Decomposition of Ireland's carbon emissions from 1990 to 2010: an extended Kaya identity. Energy Policy 59 (4-5), 573-581.

National Bureau of Statistics of China (NBSC), 2000-2016a. Chinese Energy Statistics Yearbook. China Statistics, Beijing.

National Bureau of Statistics of China (NBSC), 2000-2016b. Chinese Statistics Yearbook. China Statistics, Beijing.

Ren, S., Fu, X., Chen, X.H., 2012. Regional variation of energy-related industrial CO_2 emissions mitigation in China. China Economic Review 23 (4), 1134-1145.

Rey, S.J., 2001. Spatial empirics for economic growth and convergence. Geographical Analysis 33 (3), 195-214.

Shao, S., Liu, J.H., Geng, Y., Miao, Z., Yang, Y.C., 2016. Uncovering driving factors of carbon emissions from China's mining sector. Applied Energy 166, 220-238.

Su, B., Ang, B.W., 2017. Multiplicative structural decomposition analysis of aggregate embodied energy and emission intensities. Energy Economics 65, 137-147.

Su, B., Ang, B.W., Li, Y., 2017. Input-output and structural decomposition analysis of Singapore's carbon emissions. Energy Policy 105, 484-492.

Wang, H., Ang, B.W., Su, B., 2017a. A multi-region structural decomposition analysis of global CO_2 emission intensity. Ecological Economics 142, 163-176.

Wang, J., Zhao, T., Wang, Y., 2016a. How to achieve the 2020 and 2030 emissions targets of China: evidence from high, mid and low energy-consumption industrial sub-sectors. Atmospheric Environment 145, 280-292.

Wang, J., Zhao, T., Zhang, X., 2017b. Changes in carbon intensity of China's energy-intensive industries: a combined decomposition and attribution analysis. Natural Hazards 88(3), 1655-1675.

Wang, M., Feng, C., 2017a. Decomposition of energy-related CO_2 emissions in China: an empirical analysis based on provincial panel data of three sectors. Applied Energy 190, 772-787.

Wang, M., Feng, C., 2017b. Understanding China's industrial CO_2 emissions: a comprehensive decomposition framework. China Economics Review 166, 1335-1346.

Wang, Q.W., Hang, Y., Su, B., Zhou, P., 2018. Contributions to sector-level carbon intensity change: an integrated decomposition analysis. Energy Economics 70, 12-25.

Wang, S.J., Fang, C.L., Wang, Y., 2016b. Spatiotemporal variations of energy-related CO_2 emissions in China and its influencing factors: an empirical analysis based on provincial panel data. Renewable & Sustainable Energy Reviews 55, 505-515.

Wang, Y., Zhao, T., 2015. Impacts of energy-related CO_2, emissions: evidence from under developed, developing and highly developed regions in China. Ecological Indicators 50, 186-195.

Wang, Y., Zhu, Q., Geng, Y., 2013. Trajectory and driving factors for GHG emissions in the Chinese cement industry. China Economics Review 53, 252-260.

Wang, Z., Zhang, B., Liu, T., 2016c. Empirical analysis on the factors influencing national and regional carbon intensity in China. Renewable & Sustainable Energy Reviews 55, 34-42.

Wang, Z., Zhang, B., Yin, J., 2012. Determinants of the increased CO_2 emission and adaption strategy in Chinese energy-intensive industry. Natural Hazards 62 (1), 17-30.

Xu, B., Lin, B., 2016a. Reducing carbon dioxide emissions in China's manufacturing industry: a dynamic vector autoregression approach. Journal of Cleaner Production 131, 594-606.

Xu, J.H., Fan, Y., Yu, S.M., 2014a. Energy conservation and CO_2, emission reduction in China's 11th Five-Year Plan: a performance evaluation. Energy Economics 46 (10), 348-359.

Xu, R., Lin, B., 2016b. Why are there large regional differences in CO_2, emissions? Evidence from China's manufacturing industry. Journal of Cleaner Production 140, 1330-1343.

Xu, S.C., Han, H.M., Zhang, W.W., Zhang, Q.Q., Long, R.Y., Chen, H., He, Z.X., 2017. Analysis of regional contributions to the national carbon intensity in China in different Five-Year Plan periods. Journal of Cleaner Production 145, 209-220.

Xu, S.C., He, Z.X., Long, R.Y., 2014b. Factors that influence carbon emissions due to energy consumption in China: decomposition analysis using LMDI. Applied Energy 127 (6), 182-193.

Xu, S.C., He, Z.X., Long, R.Y., Chen, H., Han, H.M., Zhang, W.W., 2016. Comparative analysis of the regional contributions to carbon emissions in China. Journal of Cleaner Production 127, 406-417.

Xu, X.S., Zhao, T., Liu, N., Kang, J.D., 2014c. Changes of energy-related GHG emissions in China: an empirical analysis from sectoral perspective. Applied Energy 132 (11), 298-307.

Yan, X., Fang, Y.P., 2015. CO_2 emissions and mitigation potential of the Chinese manufacturing industry. Journal of Cleaner Production 103, 759-773.

Yang, J., Song, K.H., Hou, J., Zhang, P.D., Wu, J.H., 2017. Temporal and spacial dynamics of bioenergy-related CO_2 emissions and underlying forces analysis in China. Renewable & Sustainable Energy Reviews 70, 1323-1330.

Ye, B., Jiang, J.L., Li, C.S., Miao, L.X., Tang, J., 2017. Quantification and driving force analysis of provincial-level carbon emissions in China. Applied Energy 198, 223-238.

Zhang, W., Li, K., Zhou, D., Zhang, W., Gao, H., 2016a. Decomposition of intensity of energy-related CO_2 emission in Chinese provinces using the LMDI method. Energy Policy 92, 369-381.

Zhang, X., Zhao, X.R., Jiang, Z.J., Shao, S., 2017. How to achieve the 2030 CO_2 emission-reduction targets for China's industrial sector: retrospective decomposition and prospective trajectories. Global Environmental Change 44, 83-97.

Zhang, Y.J., Da, Y.B., 2015. The decomposition of energy-related carbon emission and its decoupling with economic growth in China. Renewable & Sustainable Energy Reviews 41, 1255-1266.

Zhang, Y.J., Hao, J.F., Song, J., 2016b. The CO_2 emission efficiency, reduction potential and spatial clustering in China's industry: evidence from the regional level. Applied Energy 174, 213-223.

Zhou, X., Zhang, M., Zhou, M., Zhou, M., 2017. A comparative study on decoupling relationship and influence factors between China's regional economic development and industrial energy-related carbon emissions. Journal of Cleaner Production 142 (2), 783-800.

Appendix A

Table A1. Previous LMDI efforts for provincial/regional-level carbon emissions in China.

Aggregate indicator	Main findings	Additive or multiplicative LMDI	Comparison	Reference
Carbon emissions	Driving forces of carbon emissions varied significantly across provinces while the positive effects outweighed the inhibit effects for all provinces.	Additive	Indirect	Chen and Yang (2015)
Carbon intensity	The joint effects of regional carbon intensity and economic activities Play a decisive role.	Additive	Indirect	Xu et al. (2017)
Carbon emissions	Economic growth is the dominant driver for emissions while energy intensity decreases emissions for most provinces	Additive	Indirect	Xu et al. (2016)
Carbon emissions	The economic output is the dominant positive driver while energy intensity decreases emissions most. Contribution ratios of drivers vary significantly across provinces.	Additive	Indirect	Wang and Feng (2017a)
Carbon intensity	Energy intensity is the most important role in reducing carbon intensity.	Additive	Indirect	Zhang et al. (2016)
Carbon emissions	Energy efficiency is the leading force in reducing emissions while economic or energy structure has little effect.	Additive	Indirect	Gao et al. (2016)
Carbon emissions and carbon intensity	Economic growth in central provinces needs to be low-carbon. Provinces in eastern China should be integrally planned.	Additive	Indirect	Li et al. (2016)
Carbon emissions	Economic development is the dominant driver of provincial carbon emissions. The effects of driving factors on carbon emissions varied across different provinces.	Additive	Indirect	Ding and Li (2017)
Carbon emissions	The contributions of different provinces to national carbon emissions and their driving forces differed considerably.	Additive	Indirect	Jiang et al. (2017)
Carbon emissions	The effects of economic development and energy efficiency on carbon emissions are verified across provinces	Additive	Indirect	Yang et al. (2017)
Carbon emissions	Shandong, Hebei and Jiangsu are the dominant provinces for the increase in national carbon emissions.	Additive	Indirect	Ye et al. (2017)

Table A2. Summary of studies on driving forces of carbon emissions from China's industrial sector.

Aggregate indicator	Sector	Methodology	Comparisons	Temporal or Spatial	Reference
Carbon	Industrial sector	Vector	Indirect	Spatial and	Xu and Lin (2016a)

emissions	as a whole	Autoregression		temporal	
Carbon emissions	Industrial sector as a whole	Regression analysis	Indirect	Spatial and temporal	Dong et al. (2016)
Carbon emissions	Industrial sector as a whole	STIRPAT	Indirect	Spatial and temporal	Xu and Lin (2016b)
Carbon emissions	Industrial sector as a whole	Additive LMDI	-	Temporal	Liu et al. (2007)
Carbon emissions	Industrial sector as a whole	Additive LMDI	-	Temporal	Xu and Zhao et al. (2014)
Carbon emissions	Industrial sector as a whole	Additive LMDI	-	Temporal	Yan and Fang (2015)
Carbon emissions	Industrial sector as a whole	LMDI & Scenario analysis	-	Temporal	Wang et al. (2016a)
Carbon emissions	Industrial sector as a whole	LMDI & Scenario analysis	-	Temporal	Zhang et al. (2017)
Carbon emissions	Industrial sector as a whole	Additive LMDI	Indirect	Spatial and temporal	Zhou et al. (2017)
Carbon emissions	Industrial sector as a whole	Additive LMDI	Indirect	Spatial and temporal	Ren et al. (2012)
Carbon emissions	Industrial sector as a whole	Multiplicative LMDI	Indirect	Spatial and temporal	Wang and Feng (2017b)
GHG emissions	Cement industry	Additive LMDI	-	Temporal	Wang et al. (2013)
Carbon emissions	Textile industry	Additive LMDI	-	Temporal	Lin and Moubarak (2013)
Carbon emissions	Mining sector	Additive LMDI	Indirect	Spatial and temporal	Shao et al. (2016)
Carbon emissions	Chemical process sector	Additive LMDI	Indirect	Spatial and temporal	Lin and Long (2014)

Appendix B

This paper applied the 2007 guidelines of IPCC to calculate energy-related CO_2 emissions (IPCC, 2007). The industrial CO_2 emissions from energy types *j* in province *i* in year *t* (C_{ij}^t) include three parts: the direct CO_2 emissions from fossil fuels consumption, the indirect CO_2 emissions from electricity consumption and the indirect CO_2 emissions from heat consumption. The related emissions can be calculated as follows:

$$C_i^t = \sum_j C_{ij}^t = \sum_f CF_{if}^t + CE_i^t + CH_i^t \tag{B1}$$

$$CF_{if}^t = FC_{if}^t \times EF_f \times N_f \times O_f \tag{B2}$$

$$CE_i^t = ELC_i^t \times AEF_i^t \tag{B3}$$

$$CH_i^t = HEC_i^t \times AHF_i^t \tag{B4}$$

where C_{ij}^t means the CO_2 emissions from energy types *j* (including fossil fuels, electricity and heat), measured in $MtCO_2$/yr; CF_{if}^t refers to the CO_2 emissions of province *i* from fossil fuel type *f* in year *t*, with unit of $MtCO_2$/yr;

CE_i^t is the indirect CO_2 emissions of province *i* from electricity consumption in year *t*, with unit of $MtCO_2$/yr; and CH_i^t is the indirect CO_2 emissions of province *i* from heat consumption in year *t*, with unit of $MtCO_2$/yr. FC_{if}^t is the energy consumption of fossil fuel type *f* of province *i* in year *t*, with units of 10^4 ton/yr (various gases are measured by 10^8 m^3/yr); EF_f is the emission factor of fossil fuel type *f*, with units of ton CO_2/TJ; N_f refers to net calorific value of fossil fuel type *f*, with units of TJ/10^3 ton or MJ/10^3 m^3 (details see Table B1); and O_f is carbon oxidation rate of fossil fuel type *f* (ratio values). Note that EF_f, N_f and O_f are fuel-specific but not province or time dependent (i.e., they are the same for all provinces and years). ELC_i^t refers to the electricity consumption of province *i* in year *t* (unit: 10^8 KWh/yr); HEC_i^t is the heat consumption of province *i* in year *t* (10^10 KJ/yr); AEF_i^t and AHF_i^t are average emission coefficients of electricity and heat, with the unit of Mt CO_2/KWh and Mt CO_2/KJ, respectively. The CO_2 emissions and various types of energy consumption all refer to the data set of industrial sector in province *i*.

The emission coefficient of electricity varied over the years and across provinces due to the evolving specific contributions of fossil fuels, hydro, nuclear and wind energy to power generation. Even though heat generation just depends on fossil fuels, its emission coefficient also changed across provinces and over the years because of the shifts in relative contribution of different fossil fuels. The average emission coefficients of electricity (AEF_i^t) and heat (AHF_i^t) of province *i* in year *t* can be calculated using equations (B5) and (B6):

$$AEF_i^t = \frac{\sum_f C_{i,e,f}^t}{ELG_{i,e,fossil}^t + ELG_{i,e,nuclear}^t + ELG_{i,e,renewables}^t} \tag{B5}$$

$$AHF_i^t = \frac{\sum_f C_{i,h,f}^t}{HG_{ifossil}^t} \tag{B6}$$

$C_{i,e,f}^t$ denotes the CO_2 emissions generated in province *i* by fossil fuel type *f* for electricity generation in year *t* ($MtCO_2$/yr); $ELG_{i,e,fossil}^t$, $ELG_{i,e,nuclear}^t$ and $ELG_{i,e,renewables}^t$ refer to the electricity generation in province *i* by fossil fuels, nuclear and renewables in year *t*, with the unit of 10^8 KWh/yr; $C_{i,h,f}^t$ is the CO_2 emissions generated in province *i* by fossil fuel type *f* for heat generation in year *t* ($MtCO_2$/yr); and $HG_{ifossil}^t$ is the heat generation in province *i* by fossil fuels in year *t*, with the unit of 10^10 KJ/yr.

Table B1. The oxidation rates, net calorific values, CO_2 emission factors and emission coefficients of fossil energy types.

Energy	Oxidation rate (100%)	Net calorific value (TJ/10^3 ton)	(CO_2) Emission factor (ton CO_2/TJ)	(CO_2) Emission coefficient (ton CO_2/ton)
Raw coal	0.918	20.91	94.60	1.82
Cleaned coal	0.918	26.34	98.30	2.38
Washed coal	0.918	8.36	97.90	0.75
Briquettes	0.918	15.9	97.50	1.42
Coke	0.928	28.44	107.07	2.83
Coke Oven Gas	0.990	17.99[a]	44.37	7.90[b]
Other Gas	0.990	10.45[a]	44.37	4.59[b]
Other Coking	0.928	33.46	107.07	3.32
Crude Oil	0.979	41.82	73.33	3.00
Gasoline	0.986	43.07	69.30	2.94
Kerosene	0.980	43.07	71.87	3.03
Diesel	0.982	42.65	74.07	3.10
Fuel Oil	0.985	41.82	77.73	3.20
LPG	0.989	50.18	63.07	3.13

Refinery Gas	0.989	46.06	66.73	3.04
Other Petroleum	0.979	41.87	77.33	3.17
Natural Gas	0.990	38.93[a]	56.10	21.62 [b]

Data source: IPCC (2007), NDRC (2011). Emission coefficient of fossil fuel type $f = EF_f \times N_f \times O_f$, where the variables refer to equation (B2).

[a] The unit is MJ/m^3.

[b] The unit is ton CO_2/10^4 m^3.

Appendix C

Table C1. Equations for LMDI decomposition methods.

Effect	Single-period LMDI-I decomposition	Multi-period LMDI-I decomposition
Emission coefficient effect	$EC^t_{i,effect} = \exp\left(\sum_{j=1}^{N} w_j^{p_i^t} ln \frac{EC_i^t}{EC_{hp}}\right)$	$EC^{0,t}_{i,effect} = EC^t_{i,effect} / EC^0_{i,effect}$
Energy mix effect	$EM^t_{i,effect} = \exp\left(\sum_{j=1}^{N} w_j^{p_i^t} ln \frac{EM_i^t}{EM_{hp}}\right)$	$EM^{0,t}_{i,effect} = EM^t_{i,effect} / EM^0_{i,effect}$
Energy intensity effect	$EI^t_{i,effect} = \exp\left(\sum_{j=1}^{N} w_j^{p_i^t} ln \frac{EI_i^t}{EI_{hp}}\right)$	$EI^{0,t}_{i,effect} = EI^t_{i,effect} / EI^0_{i,effect}$

The weight coefficient $w_j^{p_i^t}$ is calculated as: $w_j^{p_i^t} = \frac{L\left(C_{i,j}^t/Y_i^t, C_{hp,j}/Y_{hp}\right)}{L\left(C_i^t/Y_i^t, C_{hp}/Y_{hp}\right)}$. The function *L(x,y)* can be calculated as: $L(x,y)=\frac{y-x}{ln(y)-ln(x)}$, where $y \neq x$. If $y = x$, $L(x,y)=x$.

Table C2. IACI of targeted provinces relative to the reference province (dimensionless ratio) and ranking of that province (inside parentheses) in 1999, 2005, 2010 and 2015.

Province	1999	2005	2010	2015	Province	1999	2005	2010	2015
Beijing	0.81 (9)	0.46 (3)	0.28 (2)	0.095 (1)	Henan	1.15 (13)	1.16 (19)	0.99 (23)	0.58 (19)
Tianjin	0.79 (8)	0.60 (5)	0.38 (5)	0.19 (2)	Hubei	1.14 (12)	0.71 (7)	0.55 (10)	0.29 (6)
Hebei	1.63 (21)	1.97 (26)	1.64 (28)	1.11 (26)	Hunan	1.30 (16)	1.33 (23)	0.95 (22)	0.52 (13)
Shanxi	3.41 (30)	2.45 (29)	1.97 (29)	1.47 (28)	Guangdong	0.45 (1)	0.43 (2)	0.32 (3)	0.21 (4)
Inner Mongolia	2.81 (29)	2.06 (27)	1.50 (27)	1.33 (27)	Guangxi	1.64 (22)	1.16 (18)	0.90 (20)	0.58 (18)
Liaoning	1.59 (19)	1.11 (15)	0.84 (19)	0.60 (20)	Hainan	0.67 (4)	0.88 (11)	0.50 (7)	0.52 (14)
Jilin	1.58 (18)	1.15 (17)	0.72 (13)	0.44 (11)	Chongqing	2.39 (26)	1.13 (16)	0.81 (17)	0.56 (16)
Heilongjiang	0.99 (11)	0.57 (4)	0.36 (5)	0.26 (5)	Sichuan	1.27 (15)	0.85 (10)	0.55 (9)	0.34 (8)
Shanghai	0.56 (2)	0.37 (1)	0.24 (1)	0.20 (3)	Guizhou	2.59 (27)	2.36 (28)	1.50 (26)	0.78 (24)
Jiangsu	0.69 (5)	0.73 (8)	0.55 (8)	0.43 (10)	Yunnan	0.92 (10)	1.19 (20)	0.83 (18)	0.36 (9)
Zhejiang	0.79	0.82	0.68	0.49	Shaanxi	1.19	0.96	0.80	0.70

	(7)	(9)	(11)	(12)		(14)	(13)	(15)	(22)
Anhui	1.84	1.20	0.75	0.56	Gansu	1.67	1.48	1.20	0.89
	(25)	(21)	(14)	(17)		(23)	(25)	(24)	(25)
Fujian	0.61	0.64	0.50	0.32	Qinghai	1.71	1.21	0.91	0.72
	(3)	(6)	(6)	(7)		(24)	(22)	(21)	(23)
Jiangxi	1.62	1.05	0.81	0.63	Ningxia	2.61	4.14	3.89	3.19
	(20)	(14)	(16)	(21)		(28)	(30)	(30)	(30)
Shandong	0.72	0.92	0.70	0.52	Xinjiang	1.39	1.36	1.39	2.12
	(6)	(12)	(12)	(15)		(17)	(24)	(25)	(29)

Chapter 3

The evolution and driving forces of industrial aggregate energy intensity in China: an extended decomposition analysis[3]

Abstract: This study adopts the log-mean Divisial index (LMDI) method to decompose the changes in the industrial aggregate energy intensity (IAEI) of China into both macro and technological factors: sectoral energy intensity, industrial structure, research and development (R&D) efficiency, R&D intensity and investment intensity. Afterwards we determine the contributions of 36 industrial sub-sectors to IAEI through different factors using attribution analysis. The results show that the IAEI decreased by 38.26% from 2003 to 2015. This drop is predominantly caused by R&D efficiency (-76.01%). The sub-sectors of *ferrous metals* (-14.94%) and *non-metallic mineral products* (-13.36%) are the main contributors to the R&D efficiency effect. The sectoral energy intensity effect contributes -27.19%, mainly due to the sub-sectors of *ferrous metals* (-15.97%) and *non-ferrous metals* (-5.68%). The industrial structure effect also contributes to a decline of IAEI (-15.06%), of which, *petroleum, coking and nuclear fuel* (-5.57%) and *ferrous metals* (-4.73%) are the sub-sectors that contribute the most. Conversely, investment intensity (174.09%) and R&D intensity (52.06%) contribute to increase the IAEI, largely owing to the sub-sectors of *petroleum, coking and nuclear fuel processing, chemical materials* and *non-metallic mineral products*. Our findings suggest that the combined effects of the policies implemented during the time frame of 2003 to 2015 led to a reduction in IAEI, with R&D efficiency being the dominant factor. Nevertheless, different policies and measures should be put forward in different sub-sectors due to their varying degrees of adaptability and policy sensitivity.

Keywords: Industrial aggregate energy intensity; R&D expenditure; Investment; Index decomposition analysis; Attribution analysis.

3.1. Introduction

Over the past three decades, China has experienced a rapid economic growth with accelerating industrialization and urbanization. The expansion of industrialization and urbanization largely depended on the over-consumption of energy resources [1], with energy consumption leading inevitably to massive CO_2 emissions. China is currently the world's largest CO_2 emitter and energy consumer [2]. In response to climate change, in 2015 the Chinese government pledged to peak CO_2 emissions no later than 2030 and achieve a carbon intensity (CO_2 emissions per unit of GDP) reduction of 60-65% below 2005 levels by 2030[4]. Since energy consumption is a main source of CO_2

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[4] The government of China made the commitment to climate change in the Intended Nationally Determined Contributions in June 30, 2015.

emissions, the 13th Five-year Plan (2016-2020) calls for an energy intensity (energy consumption per unit of GDP) reduction of 15% in 2020 relative to the 2015 level.

It is well known that approximately 70% of China's total energy consumption is derived from the industrial sector [3]. In order to pursue the goal of reducing energy intensity, the Chinese government has formulated and implemented a series of policies and programs for the industrial sector. First, China published the *China Industrial Green Development Plan 2016-2020*, aiming to reduce the industrial energy intensity (energy consumption per unit of industrial value added, or IVA) by 18% in 2020 compared with the 2015 level. Second, to reduce energy consumption and improve energy efficiency, the Differential Electricity Pricing Policy (DEPP) was promulgated in energy-intensive industries in order to restrict the activity of or even eliminate altogether inefficient enterprises [4]. Dedicated programs for large and medium enterprises have also been implemented, such as the "Top-1000 Enterprises Energy Saving Program" and the "10 Key Energy Saving Projects" [5]; and energy efficiency improvements in specific industrial processes have also been planned [6]. Third, the government released several policy documents concerning adjustments in the industrial structure, such as the Guidance Catalogue of Industrial Structure Adjustment [7,8], the Decisions of Accelerating the Development of the Strategic Emerging Industries, and the Notice of the State Council on Printing and Distributing the Industrial Restructuring and Upgrading Plan [9]. Under these documents the expansion of high-pollution and high energy-consuming industries is heavily restricted, while obsolete technologies and excess capacity is phased out [10]. These policies are all in force and often directed at some specific industrial sub-sectors.

Given this context, this paper explores the factors driving industrial aggregate energy intensity (IAEI; the ratio of total industrial energy consumption to industrial value added, IVA) in general as well as the contribution of specific industrial sub-sectors, combining the log-mean Divisial index (LMDI) method [11] and attribution analysis [12]. The drivers considered are: sectoral energy intensity, industrial structure, R&D efficiency, R&D intensity and investment intensity. R&D expenditure and investment (investment on fixed capital) are not often considered when applying the LMDI model, but we believe these to be important because they play crucial roles in the adoption of energy saving technologies and production scale [13-15]. Based on the decomposition results, an attribution analysis is performed to allocate the effects of the five factors to 36 industrial sub-sectors. In this way, we can find out what aspects of each sub-sector should be improved and encouraged. In summary, this paper aims at solving three major problems: (1) identifying the underlying factors (both macro and technological factors) impacting the IAEI of China's industrial sector; (2) exploring the contribution of sub-sectors to the IAEI through each factor; (3) finding effective and practical policy implications for industrial sector to decrease the IAEI.

The rest of this paper is organized as follows. Section 3.2 makes a detailed literature review. Section 3.3 introduces the research methods and data sources. Section 3.4 shows the results of the decomposition, attribution analyses and discussion. The conclusion and policy implications are presented in Section 3.5.

3.2. Literature review

Given that 80% of CO_2 emissions in China come from energy consumption [16], it is important to understand the driving forces behind changes in energy consumption. Decomposition analysis, whereby a total change in time of a dependent variable is split as a sum of changes in independent variables, is an effective tool to understand the drivers of energy consumption [11], and the results thus obtained can also be used to evaluate the effect of the completed policies and programs [11]. There are two types of decomposition analysis: index decomposition analysis (IDA) and structural decomposition analysis (SDA) [17]. Even though the overall objective of both IDA and SDA is the same (understand the drivers of change in energy consumption or emissions), the methodological differences between IDA and SDA also lead to differences in data requirements, study scope, application features and numerical results [17]. IDA establishes a link between the dependent variable (energy consumption, for example) and production activities of different sectors. SDA, on the other hand, establishes a link between the dependent variable and consumption activities and therefore relies on the I-O model and I-O tables to study the whole economic system and capture both direct and indirect effects in supply-demand chains. In this study we are interested in the connection between the economic activity of different industrial sub-sectors and aggregate energy intensity and so we use IDA. The most popular IDA approaches are the Laspeyres and Divisia index approaches, and within the latter the arithmetic mean Divisia index (AMDI) and LMDI. The LMDI method has been widely used in previous studies due to its desirable properties of perfect decomposition and aggregation consistency [18]. Studies of the drivers of energy consumption or intensity using this approach have been conducted in different countries, such as China and India [19], EU-27 [20], across countries and sectors [21], UK [22], Switzerland [23], Iran [24] and China [25,26].

As the most energy consuming and carbon emitting sector of China, the industrial sector has been extensively studied using the LMDI method, with a focus on both CO_2 emissions and energy consumption. Xu et al. [5], Ke et al. [27], Hasanbeigi et al. [28] and Wang et al. [29] found that the industrial economic growth was the dominant factor in driving the industrial energy consumption and CO_2 emissions, while the decline in energy intensity was the major factor in the reduction of industrial energy consumption and CO_2 emissions. These studies all considered the industrial sector as a whole, whereas Wang and Feng [30], Zhou et al. [31], Ren et al. [32] and Wang et al. [33] had a regional focus, revealing that there were large differences in performances of industrial CO_2 emissions/intensity and their drivers across regions. Several studies have also examined both the industrial sector as a whole and its sub-sectors. Liu et al. [34] explored the contribution of industrial sub-sectors to the CO_2 emissions of the whole industrial sector and found that the total increase in carbon emissions was mainly caused by the energy-intensive industries. The results of Zha et al. [35] showed that the industrial structure and energy intensity had positive effects on mitigating the energy intensity and sub-sectors of *electrical machinery and equipment* and *chemical materials* were the dominant contributors. Wu and Huo [36] separately identified the driving forces of industrial sub-sectors and pointed out that existing programs of energy conservation had been effective, having led to major improvements it the energy technology efficiency of nine energy-intensive sectors. Liu et al. [9] first reorganized industrial sub-sectors into 12 aggregated sectors and then attributed the effects of factors influencing industrial carbon intensity to these 12 aggregated sectors, finding that *chemicals*, *iron and steel*, *metal and machinery*, and *cement and ceramics* were the most important sub-sectors. Some specific industrial sub-sectors including *chemicals*, *cement*, *textiles*, *nonferrous metals*, and *iron and steel* have also been studied separately by Lin and Tan [37], Lin and Long [38], Wang et al. [39], Lin and Moubarak [40], Wang and Feng [41] and Zhang et al. [42]. The drivers in the above-mentioned literature are usually confined to several conventional factors, such as emission coefficient, energy intensity, industrial structure, energy structure [5] and economic activities (see Table A1). China's economic growth over the past decades has been driven by investment and so a few studies have used the LMDI method considering technological factors caused by R&D expenditure and fixed asset investment as drivers of emissions. Shao et al. [13] took the lead in introducing technological factors (R&D efficiency, R&D intensity and investment intensity) in the LMDI model, exploring their effects on industrial CO_2 emissions of Shanghai. Following their work, Zhang et al. [15] considered both macro and technological factors in their decomposition of industrial carbon intensity (of both energy- and process-related CO_2 emissions) of China from 1993 to 2014. These two studies found that the technological factors had significant effects on industrial CO_2 emissions (intensity) of Shanghai (China).

Due to the heterogeneity of industrial sub-sectors, it is important to understand the contribution of different sub-sectors to the performance of industrial energy consumption and CO_2 emissions as a whole. The combination of the multiplicative LMDI method and attribution analysis makes such research possible. The multiplicative LMDI analysis can be used to decompose the ratio change of an aggregate indicator, and the decomposition results are expressed in indices [18]. Because the results of multiplicative decomposition do not satisfy the "additivity principle" for sectors, Choi and Ang [12] proposed the use of attribution analysis to quantify the contribution of each individual sub-sector to the overall percent change of factors. Thus, attribution analysis can be regarded as a complement to the multiplicative decomposition analysis of a ratio change (i.e., carbon intensity or energy intensity). Attribution analysis can reveal which sub-sectors are the dominant contributors to the change in the index and thus where regulation through policies and measures is likely to have a higher impact. Such studies have already been conducted in several countries and regions, such as Mexico [44], Europe [45,46], Korea [47,48] and Spain [49]. In the case of China, Wang et al. [50], Liu et al. [9] and Wang et al. [51] have studied the carbon intensity of China, the industrial sector and energy-intensive industries, respectively. Although they did not attribute the influencing factors to sub-sectors, Liu et al. [52] and Wang et al. [53] attributed environmental changes to different provinces of China.

Previous studies of the industrial sector using LMDI are summarized in Table A1. There are still some gaps in the current literature, in particular a detailed discussion of the relationship between industrial sector as a whole and its sub-sectors. Among previous studies, only a few have attempted to do so, as mentioned above, including Liu et al. [9], Liu et al. [34], Zha et al. [35] and Wu and Huo [36]. However, Liu et al. [34] and Wu and Huo [36] failed to allocate the effects to each industrial sub-sector. In contrast, Zha et al. [35] and Liu et al. [9] have addressed this matter, but some gaps still exist. Zha et al. [35] used the proportion of IVA in each sub-sector in total IVA to allocate the factor effects to sub-sectors, while Liu et al. [9] reorganized industrial sub-sectors into 12 aggregate sectors, thus possibly losing detailed information of specific sub-sectors. Moreover, only conventional factors were included in their studies (emissions coefficient, energy intensity and industrial structure) and technological factors were not considered. However, according to Fisher-Vanden et al. [54], R&D activities are directly relevant to innovation and investment is also an important part of the industry sector's activity [13]. Enterprises can direct R&D expenditure and investment to promote energy-

[5] Yang et al. [43] discussed the improvement pathway of energy structure in China's industrial sector at the level of both the industry as a whole and sub-sectors.

saving and emission-mitigation technologies as well as to update production equipment and expand production scale. The Chinese government stated in the *National Plan on Climate Change (2014-2020)* that R&D expenditure in the industrial sector should be promoted. Whether investment activities should be carried out in all industrial sub-sectors is worth studying, because not all investment is likely to have the same energy-saving impacts. Therefore, it is important to incorporate R&D expenditure and investment in the Kaya identity [13,15] so as to get a better understanding of how R&D expenditure and investment behave in the industrial sector and sub-sectors.

This paper aims to fill these research gaps by developing a comprehensive model, which integrates an extended LMDI method and attribution analysis into a common framework, in which the IAEI of China in the period 2003-2015 is decomposed into both macro and technological factors. As far as we are aware this has never been done before. The extended LMDI is used to decompose the IAEI into both macro and technological factors. The contributions of sub-sectors to IAEI through each factor are studied based on attribution analysis. The attribution analysis can expose the detailed relationship between the influencing factors and sub-sectors, which is extremely significant to assist policymaking, since the sensitivity and adaptability of industrial sub-sectors to energy and environmental policies are specified. The results thus obtained can be used to test the effectiveness of energy-related policies. We hope that our results may contribute to bring forward effective and practical policy implications to reduce the IAEI of China’s industrial sector as well as its sub-sectors.

3.3. Methods and data sources

3.3.1. The extended LMDI method

Following Shao et al. [13] and Zhang et al. [15], we decomposed the changes in IAEI (the ratio of total industrial energy consumption to industrial value added, IVA) into the effects of sectoral energy intensity, industrial structure, R&D efficiency, R&D intensity and investment intensity. Among these, the sectoral energy intensity and industrial structure are factors usually considered and we call them macro-factors. IAEI may misrepresent the actual phenomena happening in each sub-sector [55]. Therefore, when investigating the driving factors of the IAEI, the sectoral energy intensity is often considered as a measure of true intensity change and has been widely used to track sectoral energy efficiency trends [12]. Since 1970s, changes in industrial structure have played an important role in shaping the trend of IAEI [56], so we considered this factor in the present paper.

The last three factors (i.e., other than sectoral energy intensity and industrial structure) are technological factors and rarely considered before. R&D expenditure is the main indicator of innovation inputs to industrial production, as it can be usually required to develop new technologies and products [54]. If R&D expenditure is used to develop energy-saving technologies, it will result in improvements in energy efficiency. The energy-saving effect of R&D expenditure is manifested in energy intensity, which has been always considered as the measurement of technology in decomposition analysis. Besides, fixed assets investment, as capital input for different industrial sub-sectors, is mainly used for new construction, expansion, reconstruction and technological transformation, as well as equipment purchase, which can lead to scale expansion or energy saving. The energy-saving effect of investment is also reflected in sectoral energy intensity. Even though improving energy efficiency through the adoption of efficient technologies is regarded as an effective way to conserve energy [57], it has been observed that the expected efficiency gains are often not fully realized in practice due to the rebound effect. This happens when energy efficiency improvements lead to a new round of economic growth (output increase) and decrease the effective cost of an energy service, therefore leading in turn to more energy consumption [58,59]. This increase might (partially) offset the expected savings in energy consumption derived from energy efficiency improvements. Therefore, it is important to study the effects of these five factors on IAEI.

To do so, assuming that there are *N* sectors, the IAEI in China in the year *t* can be written as follows:

$$IAEI^t = \frac{E^t}{Y^t} = \sum_{i=1}^{N} \frac{E_i^t}{Y_i^t} \times \frac{Y_i^t}{R_i^t} \times \frac{R_i^t}{F_i^t} \times \frac{F_i^t}{Y_i^t} \times \frac{Y_i^t}{Y^t} = \sum_{i=1}^{N} SEI_i^t \times RE_i^t \times RI_i^t \times FI_i^t \times IS_i^t \tag{1}$$

where E^t and Y^t are, respectively, total industrial energy consumption, measured in million tons coal equivalent per year (Mtce/yr), and IVA of the industrial sector as a whole, with unit of billion yuan/yr, in year *t*; E_i^t and Y_i^t are, respectively, the energy consumption (Mtce/yr) and IVA (billion yuan/yr) of sub-sector *i* in year *t*; R_i^t is the R&D expenditure of sub-sector *i* in year *t*, measured in billion yuan/yr; F_i^t is the investment of sub-sector *i* in year *t*, with unit of billion yuan/yr; SEI_i^t is the sectoral energy intensity factor of sub-sector *i* in year *t* (Mtce/billion yuan); RE_i^t represents the R&D efficiency factor of sub-sector *i* in year *t* (unit: billion yuan/billion yuan); RI_i^t provides the R&D intensity factor of sub-sector *i* in year *t* (unit: billion yuan/billion yuan); FI_i^t is the investment intensity factor of sub-sector *i* in year *t* (unit: billion yuan/billion yuan); and IS_i^t is the industrial structure factor of sub-sector *i* in year *t* (unit: billion yuan/billion yuan).

There are two standard multiplicative LMDI methods, defined by the weights formulae used, the Montgomery-Vartia index (LMDI-I) and Sato-Vartia index (LMDI-II) [60]. The LMDI-II method is employed in this paper. In a single-period LMDI decomposition, the ratio change *DA* of the IAEI between two consecutive years [*t*-1, *t*] is expressed as follows [11]:

$$DA = \frac{IAEI^t}{IAEI^{t-1}} = SEI^{t-1,t} \times RE^{t-1,t} \times RI^{t-1,t} \times FI^{t-1,t} \times IS^{t-1,t} \tag{2}$$

$SEI^{t-1,t}$, $RE^{t-1,t}$, $RI^{t-1,t}$, $FI^{t-1,t}$, and $IS^{t-1,t}$ are effects of sectoral energy intensity, industrial structure, R&D efficiency, R&D intensity and investment intensity. These five effects can be calculated using the Sato-Vartia weight coefficient, which is shown in Table A2 in Appendix. We can obtain the results of the multi-period LMDI on the basis of the single-period LMDI using the equations listed in Table A2.

The detailed description of sectoral energy intensity, industrial structure, R&D efficiency, R&D intensity and investment intensity effects is as follows:

Sectoral energy intensity (SEI) effect: The sectoral energy intensity is the ratio of energy consumption in a sub-sector to its IVA and reflects the energy efficiency of each sub-sector. The higher the energy intensity, the lower the energy efficiency, and the more energy will be consumed by an energy system for the same unit of output.

Industrial structure (IS) effect: The industrial structure is defined as the ratio between IVA of a specific sub-sector and industrial aggregate IVA, which can be used to reflect the scale shifts among specific sub-sectors. If the share of high energy-consuming sub-sectors in the whole industrial sector increases, there is an increase in energy consumption.

R&D efficiency (RE) effect: The R&D efficiency is the ratio of IVA to R&D expenditure of industrial sub-sectors, which can identify whether there is a production-expanding effect of R&D expenditure. If there are increasing returns to scale in R&D expenditure, it will lead to an increase in output and energy consumption. Also, R&D expenditure can be used to develop new technologies, which may contribute to energy saving. This energy-saving effect of R&D expenditure is manifested in sectoral energy intensity.

R&D intensity (RI) effect: R&D intensity is the ratio of R&D expenditure to investment. R&D expenditure is always related to the innovation on technology or products, while investment is to purchase fixed assets. Therefore, the R&D intensity reflects the degree of innovation embodied in investment. The higher the value of R&D intensity, the stronger the technology or product innovation, leading to economic growth and higher energy consumption.

Investment intensity (FI) effect: The investment of China's industrial sector increased at an annual average growth rate of 24.31% (current price) from 2003 to 2015 [61], which may result in over-investment or over-capacity. Over-investment and build-up of over-capacity lead to extra energy consumption but not to additional output. This paper uses the investment intensity (ratio of investment to IVA) to reflect the effect of over-investment or over-capacity. The greater the value of investment intensity, the more energy will be consumed.

3.3.2. Attribution analysis

After having quantified the effects of sectoral energy intensity ($SEI^{t-1,t}$), R&D efficiency ($RE^{t-1,t}$), R&D intensity ($RI^{t-1,t}$), investment intensity ($FI^{t-1,t}$) and industrial structure ($IS^{t-1,t}$) on changes in IAEI, we performed an attribution analysis to address the sectoral heterogeneities in driving forces, in both single-year and multi-year periods. Single-year period attribution analysis is performed as follows [12]:

$$SEI^{t-1,t} - 1 = \sum_{i=1}^{N} E_{SEI,i}^{t-1,t} = \sum_{i=1}^{N} \frac{\frac{w_i^{s-v}}{L\left(SEI_i^{t-1} SEI^{t-1,t}, SEI_i^{t}\right)} SEI_i^{t-1}}{\sum_{i=1}^{N} \frac{w_i^{s-v}}{L\left(SEI_i^{t-1} SEI^{t-1,t}, SEI_i^{t}\right)} SEI_i^{t-1}} \left(\frac{SEI_i^t}{SEI_i^{t-1}} - 1\right) \tag{3a}$$

$$RE^{t-1,t} - 1 = \sum_{i=1}^{N} E_{RE,i}^{t-1,t} = \sum_{i=1}^{N} \frac{\frac{w_i^{s-v}}{L\left(RE_i^{t-1} RE^{t-1,t}, RE_i^{t}\right)} RE_i^{t-1}}{\sum_{i=1}^{N} \frac{w_i^{s-v}}{L\left(RE_i^{t-1} RE^{t-1,t}, RE_i^{t}\right)} RE_i^{t-1}} \left(\frac{RE_i^t}{RE_i^{t-1}} - 1\right) \tag{3b}$$

$$RI^{t-1,t} - 1 = \sum_{i=1}^{N} E_{RI,i}^{t-1,t} = \sum_{i=1}^{N} \frac{\frac{w_i^{s-v}}{L\left(RI_i^{t-1} RI^{t-1,t}, RI_i^{t}\right)} RI_i^{t-1}}{\sum_{i=1}^{N} \frac{w_i^{s-v}}{L\left(RI_i^{t-1} RI^{t-1,t}, RI_i^{t}\right)} RI_i^{t-1}} \left(\frac{RI_i^t}{RI_i^{t-1}} - 1\right) \tag{3c}$$

$$FI^{t-1,t} - 1 = \sum_{i=1}^{N} E_{FI,i}^{t-1,t} = \sum_{i=1}^{N} \frac{\frac{w_i^{s-v}}{L\left(FI_i^{t-1} FI^{t-1,t}, FI_i^{t}\right)} FI_i^{t-1}}{\sum_{i=1}^{N} \frac{w_i^{s-v}}{L\left(FI_i^{t-1} FI^{t-1,t}, FI_i^{t}\right)} FI_i^{t-1}} \left(\frac{FI_i^t}{FI_i^{t-1}} - 1\right) \tag{3d}$$

$$IS^{t-1,t}-1=\sum_{i=1}^{N}E_{IS,i}^{t-1,t}=\sum_{i=1}^{N}\frac{\frac{w_i^{s-v}}{L\left(IS_i^{t-1}IS^{t-1,t},IS_i^{t}\right)}IS_i^{t-1}}{\sum_{i=1}^{N}\frac{w_i^{s-v}}{L\left(IS_i^{t-1}IS^{t-1,t},IS_i^{t}\right)}IS_i^{t-1}}\left(\frac{IS_i^{t}}{IS_i^{t-1}}-1\right) \tag{3e}$$

where $E_{SEI,i}^{t-1,t}$, $E_{RE,i}^{t-1,t}$, $E_{RI,i}^{t-1,t}$, $E_{FI,i}^{t-1,t}$ and $E_{IS,i}^{t-1,t}$ respectively denotes the contribution of sub-sector i to the percent change of $SEI^{t-1,t}$, $RE^{t-1,t}$, $RI^{t-1,t}$, $FI^{t-1,t}$ and $IS^{t-1,t}$ from year t-1 to year t; w_i^{s-v} is the Sato-Vartia index weight, which can be calculated by the equations in Appendix A. The multi-year period attribution analysis is derived from the single-year period and the equations are listed in Table A3 in Appendix.

3.3.3. Data description

The data set of this study is related to the 36 industrial sub-sectors (Table A4) of China from 2003 to 2015. The final energy consumption data of industrial sub-sectors were collected from the China Energy Statistical Yearbook [3]. The IVA data from 2003 to 2007 were collected from the China Statistical Yearbook [62]. Since the IVA data for industrial sub-sectors were only published before 2007, the data of 2008-2015 were calculated using the officially reported annual average growth rates of IVA from the website of National Bureau of Statistics of China [63], as validated by [9] and [27]. R&D expenditure and investment data were also collected from the website of National Bureau of Statistics of China [63]. All monetary-related values were converted to 1996 constant price using price indices [62].

3.4. Results and discussion

3.4.1. Results of decomposition analysis

The single- and multi-period decomposition results of China's IAEI are illustrated in Fig. 1 and Fig. 2, respectively. The single-period decomposition results show that the IAEI of China's industrial sector decreased during the whole study period except for 2004-2005 and 2011 even though it cumulatively dropped by 38.26% over the study period. The decrease in IAEI indicates an improvement in energy efficiency. In this paper, changes in IAEI are determined by the interaction of the sectoral energy intensity, R&D efficiency, R&D intensity, investment intensity and industrial structure.

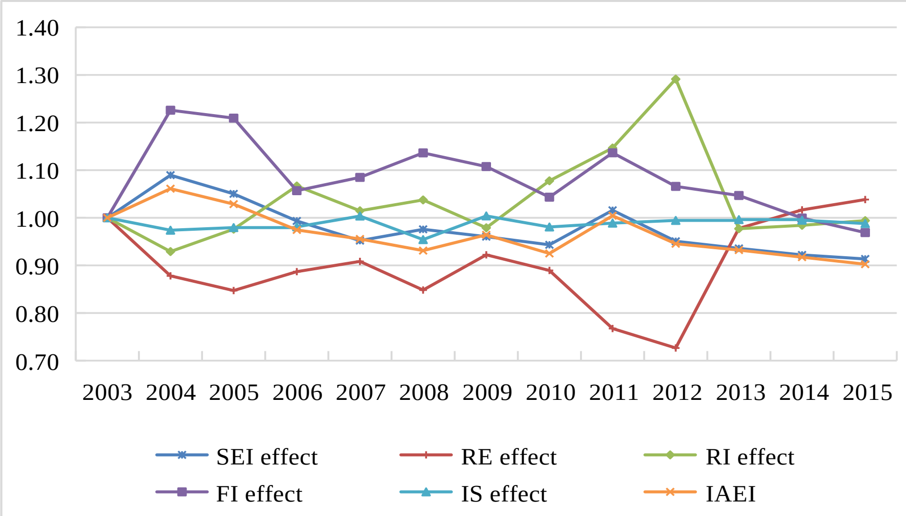

Fig. 1. Single-period decomposition results of changes in IAEI (base year = previous year). The IAEI is industrial aggregate energy intensity. SEI, RE, RI, FI and IS respectively represents sectoral energy intensity, R&D efficiency, R&D intensity, investment intensity and industrial structure. The y axis gives a dimensionless ratio compared to the previous year.

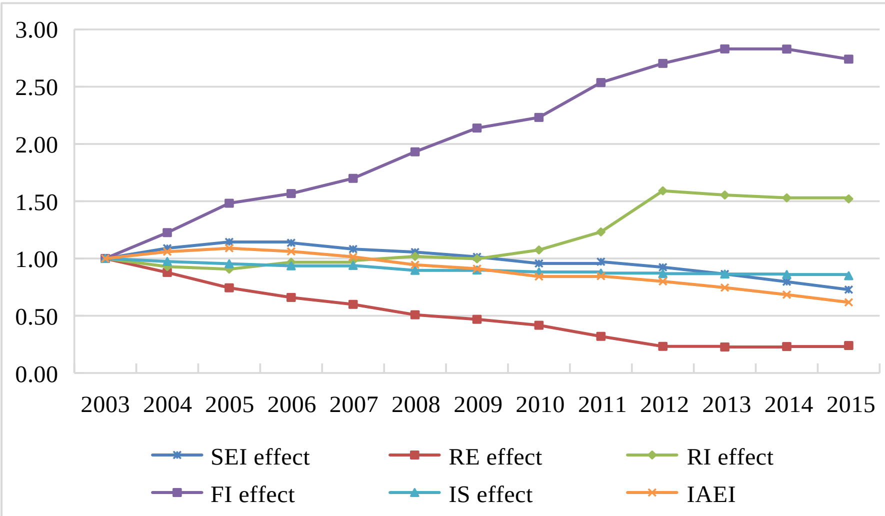

Fig. 2. Multi-period decomposition results of changes in IAEI (base year = 2003). The IAEI is industrial aggregate energy intensity. SEI, RE, RI, FI and IS respectively represents sectoral energy intensity, R&D efficiency, R&D intensity, investment intensity and industrial structure. The results are given as dimensionless ratios compared to the base year (2003).

R&D efficiency was the dominant factor in the decrease of IAEI (contribution of 76.01%). This indicates that there were decreasing returns to scale in R&D expenditure, or that R&D expenditure was primarily targeted at energy conservation instead of expanding the production scale (as reflected in the sectoral energy intensity factor). The single-period decomposition results show that from 2004 to 2013 R&D efficiency contributed to a decrease in IAEI while in 2014 and 2015 it contributed to an increase, indicating that the production resources have been optimized and R&D expenditure exhibits increasing returns to scale. As a response to this trend, the Chinese government is calling in recent years for the shift from an investment-driven to an innovation-driven mode of economic growth [64].

Both sectoral energy intensity and industrial structure contributed to a decrease in IAEI from 2003 to 2015 (respective contributions of 27.19% and 15.06%). Herein, industrial structure contributed to mitigate IAEI during the whole study period except in 2007 and 2009, while sectoral energy intensity contributed to increase the IAEI in 2004, 2005 and 2011. The effect of sectoral energy intensity can be explained by the joint effects of a decrease in energy intensity (or improvement in energy efficiency) by industrial sub-sectors. Since 1995, the formulation and strict implementation of energy-conservation policies led to a decrease in the energy intensity of many industrial sub-sectors. The decline in sectoral energy intensity of 30 sub-sectors lead to the decrease of IAEI. To understand why sectoral energy intensity contributed to an increase in IAEI in some specific years, it is important to recall that in 2001 China joined the WTO (World Trade Organization), and that in 2008 there was an economic crisis. When China acceded to the WTO and the export market opened up, there was a rapid expansion in the scale of industrial production. The control of energy consumption was not a major governmental concern in those years, and the energy intensity of twenty-two sub-sectors increased in 2004 and 2005. Even though the government began to pay attention to energy conservation and issue policies on the subject around that time, the effects of those policies lagged behind. For example, the policies of “10 Key Energy Saving Projects” and “Differential Electricity Pricing Policy” were issued in 2004 and the “Top-1000 Enterprises Energy Saving Program” and the improvement of energy efficient in industrial processes were issued in 2006 [4-6]. Under these policies, the energy intensity of most sub-sectors began to decline since 2006. The economic crisis of 2008 greatly affected the rapid economic growth of China, so local governments stimulated economic development by reducing the power tariff and increasing the export tax rebate rates of industrial products, which lead to a short-term increase in sectoral energy intensity. The decline in IAEI caused by industrial structure was mainly due to the decrease in IVA share of most high energy-consuming sub-sectors.

In stark contrast to the above-mentioned three effects, the R&D intensity and investment intensity contributed to an increase of IAEI with the values of 52.06% and 174.09%, respectively. It can be seen from the single period decomposition results that the effects of these two factors were mixed and seemed to improve as time went on. The positive effect of R&D intensity indicates the innovation promoted by R&D expenditure resulted in an increase of production scale. The large and positive impact of investment intensity shows that the investment has grown much faster than economic output during the whole study period: from 2003 to 2015, the IVA tripled, while investment increased tenfold. This suggests that there might have been an inefficient allocation of production factors caused by overinvestment, leading to excess energy consumption.

3.4.2. Results of the attribution analysis

Table 1. Multi-period attribution results of SEI, RE, RI, FI and IS in 2015 (base year = 2003; unit: %): Contribution of each sub-sector to the multi-period effects of SEI, RE, RI, FI and IS.

Sector	SEI	RE	RI	FI	IS	Sector	SEI	RE	RI	FI	IS
S_1	-1.81	-2.46	0.63	3.40	-0.74	S_{19}	-4.85	-11.33	4.50	28.52	-0.13
S_2	-0.05	-1.90	0.31	3.00	-2.01	S_{20}	-0.59	-0.40	0.23	1.48	0.08
S_3	-0.50	-0.75	0.92	0.46	0.31	S_{21}	-0.95	-0.80	0.39	1.01	0.00
S_4	-0.34	-0.16	-0.09	0.85	0.08	S_{22}	0.56	-0.85	1.40	1.91	-0.20
S_5	-0.39	-0.25	-0.84	2.26	-0.07	S_{23}	8.81	-2.63	6.75	10.47	-0.71
S_6	-0.35	-2.17	1.04	5.83	-0.20	S_{24}	3.84	-13.36	17.78	40.82	-0.30
S_7	-0.46	-0.65	0.27	2.13	-0.03	S_{25}	-15.97	-14.94	10.48	7.35	-4,73
S_8	-0.40	-0.52	-0.49	2,03	-0.05	S_{26}	-5.68	-3.90	1.93	6.73	1.34
S_9	-0.15	-0.05	0.06	-0.01	-0.05	S_{27}	-0.77	-1.95	2.24	4.72	0.05
S_{10}	-1.19	-2.34	1.01	5.79	-0.57	S_{28}	-1.22	-0.80	-1.18	4.47	0.16
S_{11}	-0.09	-0.18	-0.06	1.32	-0.08	S_{29}	-0.29	-0,57	-0.05	2.95	0.14
S_{12}	-0.03	-0.20	0.11	0.82	-0.05	S_{30}	-1.63	-0.50	-1.75	2.80	0.18
S_{13}	-0.37	-0.26	-0.02	1.67	0.20	S_{31}	-0.33	-0.45	-0.75	3.01	0.08
S_{14}	-0.02	-0.19	0.13	0.39	0.01	S_{32}	-0.27	-0.31	-0.18	1.71	0.09
S_{15}	-1.16	-1.32	1.05	3.18	-0.34	S_{33}	-0.11	-0.11	0.05	0.31	0.01
S_{16}	-0.18	-0.08	-0.01	0.47	-0.03	S_{34}	-2.77	-0.98	0.82	7.26	-1.75
S_{17}	-0.01	-0.16	0.02	0.70	-0.02	S_{35}	-0.41	0.18	0.06	0.23	0.13
S_{18}	2.76	-8.55	5.29	12.53	-5.57	S_{36}	0.18	-0.11	0.02	1.49	-0.32
						Total change (%)	-27.19	-76.01	52.06	174.09	-15.06

Note: SEI, RE, RI, FI and IS respectively represents sectoral energy intensity, R&D efficiency, R&D intensity, investment intensity and industrial structure. The full name of each sub-sector refers to Table A4.

The percent change of sectoral energy intensity can be further attributed to the 36 industrial sub-sectors using attribution analysis. As shown in Table 1, the multi-period results show that five sub-sectors contributed to the increases in IAEI through sectoral energy intensity from 2003 to 2015, especially the sub-sectors of *petroleum, coking and nuclear fuel* (S_{18}), *plastic products* (S_{23}) and *non-metallic mineral products* (S_{24}) with values of 2.76%, 8.81% and 3.84% respectively, reflecting the fact that the energy efficiency of these three sectors did not improve and the implemented energy policies did not work for them. The sub-sector of *ferrous metals* (S_{25}) was the dominant contributor to a decrease of IAEI with the value of -15.97% through the sectoral energy intensity factor throughout the duration of the study period, followed by the sub-sectors of *non-ferrous metals* (S_{26}) (-5.68%) and *chemicals* (S_{19}) (-4.85%). This result indicates that the policies for improving energy efficiency in these three industrial sub-sectors in China achieved the desired results. Fig. 3 shows the results of the single-period attribution analysis, where we can see that sectoral energy intensity contributed to a reduction of IAEI except in 2004, 2005 and 2011. The short-term growth of IAEI caused by sectoral energy intensity mainly came from the sub-sectors of *petroleum, coking and nuclear fuel* (S_{18}), *chemicals* (S_{19}), and *non-metallic mineral products* (S_{24}) and *ferrous metals* (S_{25}). This can be explained by the rapid expansion of urbanization and industrialization, which resulted in a sudden expansion in the demand of the products of these industrial sub-sectors and a lot of energy consumption [65].

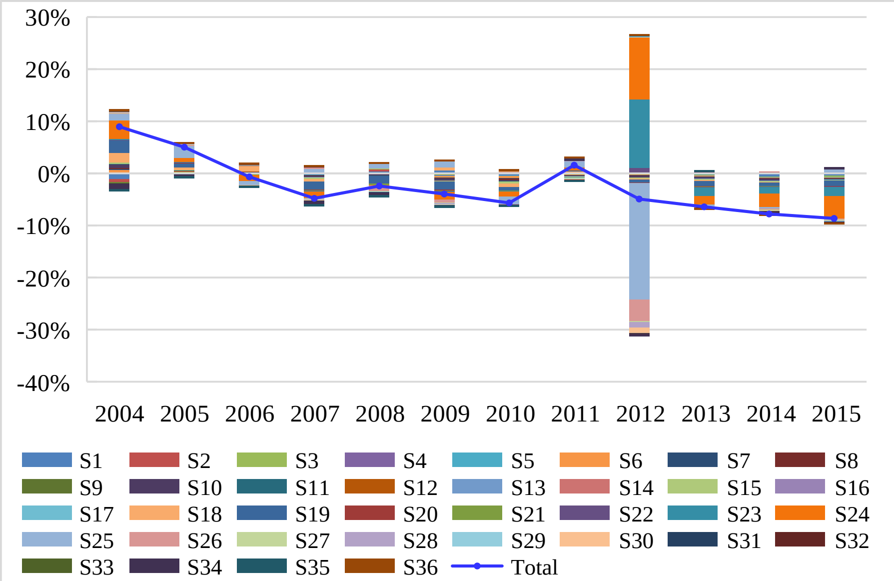

Fig. 3. Single-period attribution results of sectoral energy intensity effect. The y-axis gives the % contribution of each industrial sub-sector to the sectoral energy intensity effect. The full name of each sub-sector refers to Appendix A, Table A4. Results in Table format can be found in Appendix B,Table B1.

Tables 1 and Fig.4 show the multi- and single-period attribution results of R&D efficiency, which was most important factor contributing to a decline in IAEI. This phenomenon can be explained by that China has vigorously increased R&D expenditure devoted to energy savings and emission mitigation in recent years, with an annual average growth rate of 21.94% over the study period. Over the whole period, the cumulative contribution of R&D efficiency reached -76.01%. Table 1 shows that the top three sub-sectors contributing to this negative value were *ferrous metals* (S_{25}) (-14.94%), *non-metallic mineral products* (S_{24}) (-13.36%) and *chemicals* (S_{19}) (-11.33%). These three sub-sectors all belong to the sub-category of energy-intensive industries, exhibiting high energy consumption and high emissions. Because the sectoral energy intensity of the sub-sector of *non-metallic mineral products* (S_{24}) contributed to an increase in IAEI and the R&D efficiency contributed to a decrease in IAEI, this means that there were decreasing returns to scale in R&D expenditure in that sub-sector S_{24}. Most sub-sectors contributed to the decline in IAEI through sectoral energy intensity except for the sub-sector pf *gas production and supply* (S_{35}) (0.18%). From the line in Fig. 4, it can be seen that R&D efficiency contributed significantly to increase IAEI in 2014 and 2015. This increase was mainly caused by the sub-sectors of *non-metallic mineral products* (S_{24}) and *coal mining and washing* (S_1). That means the R&D expenditure resulted in a large increase of output in these two sub-sectors.

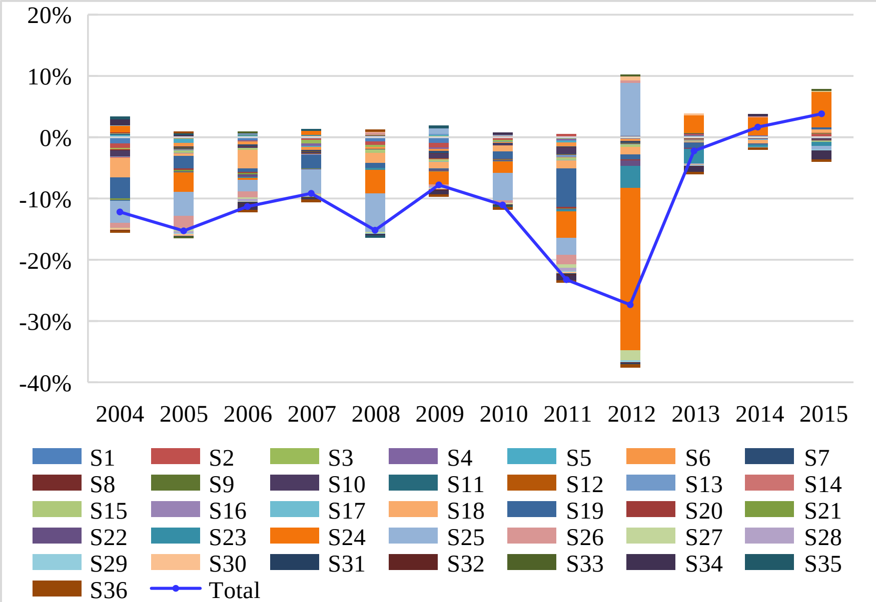

Fig. 4. Single-period attribution results of R&D efficiency effect. The y-axis gives the % contribution of each industrial sub-sector to the R&D efficiency effect. The full name of each sub-sector refers to Appendix A, Table A4. Results in Table format can be found in Appendix B, Table B2.

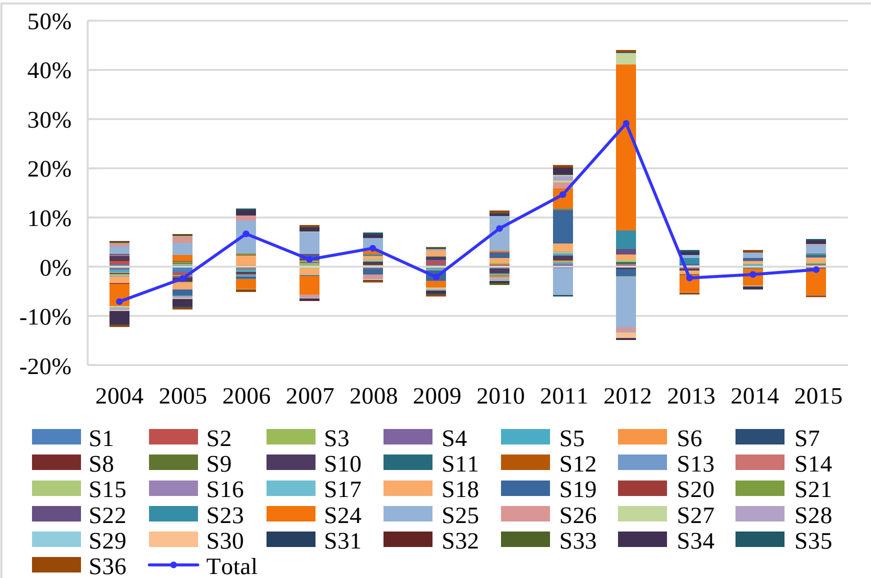

Fig. 5. Single-period attribution results of R&D intensity effect. The y-axis gives the % contribution of each industrial sub-sector to the R&D intensity effect. The full name of each sub-sector refers to Appendix A, Table A4. Results in Table format can be found in Appendix B, Table B3.

Table 1 and Fig.5 show the multi- and single-period attribution results of R&D intensity, respectively. Contrary to what happened with sectoral energy intensity and R&D efficiency, the accumulated contribution of R&D intensity to IAEI was 52.06% from 2003 to 2015. This positive contribution was mainly due to the sub-sectors of *non-metallic mineral products* (S_{24}), *ferrous metals* (S_{25}) and *plastic products* (S_{23}), which contributed respectively with 17.78%, 10.48% and 6.75%. The fact that R&D intensity contributed to increase IAEI means that the innovation associated with R&D expenditure lead to increases in output. It should be emphasized that there were more than ten sub-sectors in which R&D intensity contributed to a decrease in IAEI, such as *general equipment manufacturing* (S_{28}), *transportation equipment manufacturing* (S_{30}) and *non-metallic mineral extraction and mining* (S_5); however, this negative contribution of specific sub-sectors did not offset the overall positive contribution. Even though the multi-period analysis showed that R&D intensity contributed to an increase in IAEI, the single-period attribution analysis shows that this effect was reversed in 2004, 2005, 2009, 2013, 2014 and 2015.

Table 1 and Fig.6 illustrate the multi- and single-period attribution analysis of investment intensity. The last line in Table 1 shows that the investment intensity contributed to an increase in IAEI of 174.09%. All industrial sub-sectors contributed to increase IAEI. *non-metallic mineral products* (S_{24}), *chemical materials and products* (S_{19}) and *petroleum, coking and nuclear fuel* (S_{18}) were the top three sub-sectors, in terms of a positive contribution to IAEI through investment intensity, with values of 40.82%, 28.52% and 12.53%. The single-period attribution analysis shows that the R&D intensity contributed to an increase in IAEI in all years except 2014 and 2015. In 2014 and 2015, some sub-sectors contributed to a decrease in IAEI, among which *petroleum, coking and nuclear fuel* (S_{18}), *chemical materials and products* (S_{19}) and *ferrous metals* (S_{25}) ranked in the top three.

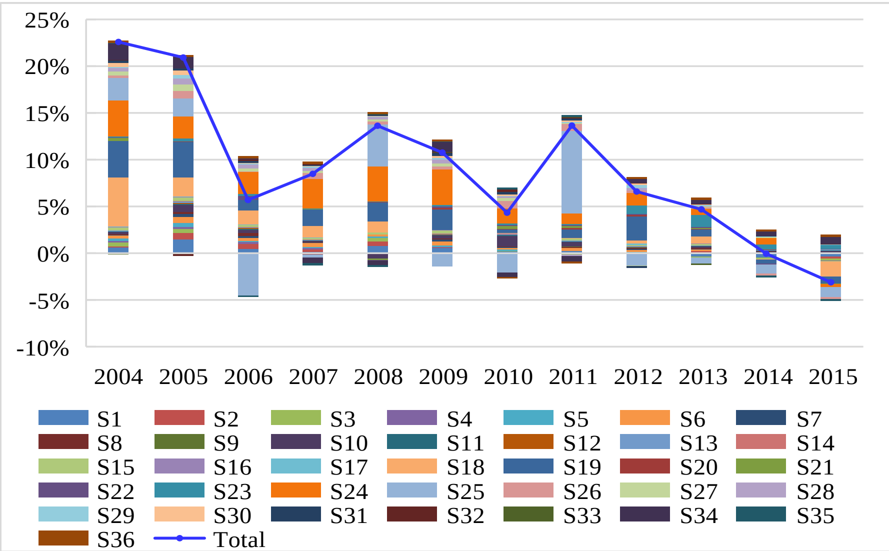

Fig. 6. Single-period attribution results of investment intensity effect. The y-axis gives the % contribution of each industrial sub-sector to the investment intensity effect. The full name of each sub-sector refers to Appendix A, Table A4. Results in Table format can be found in Appendix B, Table B4.

The attribution results of industrial structure are illustrated in Table 1 (multi-period) and Fig.7 (single-period). The results provide additional detailed information on which sub-sectors were the main sources of change in IAEI through industrial structural change. As shown in Fig.7, the impact of industrial structure on aggregate energy intensity was negative except for 2007 and 2009, which was mainly caused by the *chemical* (S_{19}) and *non-metallic* (S_{24}) sub-sectors, because the IVA proportion of these two sub-sectors in total IVA increased to some extent in 2007 and 2009. From Table 1, it can be seen that the contributions of most sectors were negative from 2003 to 2015, while the industrial structure change of the *non-ferrous metals* sub-sector (S_{26}) contributed to increase IAEI. The fast growth in these three industries (S_{19}, S_{24} and S_{26}) may be the result of the rapid industrialization and urbanization in China recent years. An increased amount of non-ferrous materials was mass produced to meet the demand of the automobile production, real estate industry and other infrastructure construction [60]. With the rapid development of network applications in China, the demand for electronic equipment is also increasing rapidly. The sub-sectors of *petroleum, coking and nuclear fuel* (S_{18}), *ferrous metals* (S_{25}) and *oil and gas extraction* (S_2) were the main contributors to the decrease of IAEI through the factor of industrial structure, with values of -5.57%, -4.73% and -2.01%, respectively.

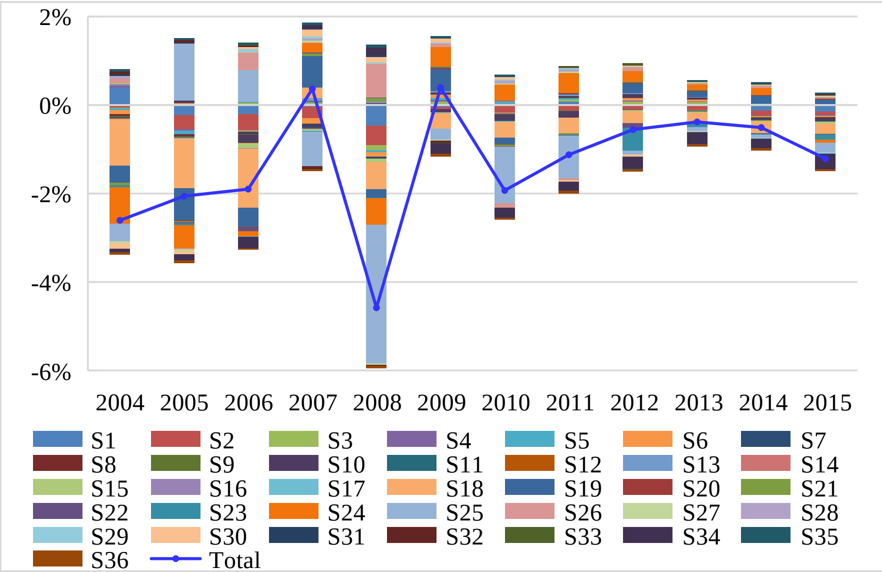

Fig. 7. Single-period attribution results of industrial structure effect. The y-axis gives the % contribution of each industrial sub-sector to the industrial structure effect. The full name of each sub-sector refers to Appendix A, Table A4. Results in Table format can be found in Appendix B, Table B5.

3.4.3. Discussion

Most previous studies pointed out that sectoral energy intensity was the dominant factor to determine the evolution of aggregate energy intensity [8,12,35,36]. However, when the technological factors of R&D efficiency, R&D intensity and investment intensity are included in the decomposition, the results become different. According to the decomposition and attribution results obtained, the R&D

efficiency and investment intensity were respectively the dominant factor to decrease and increase IAEI. These results are in line with the investment-driven economic development of China in past few years. The contribution of R&D efficiency to the decrease in IAEI means there were decreasing returns to scale in R&D investment. The increase in IAEI caused by investment intensity indicates that the investment efficiency in output can be improved. Additionally, the R&D intensity also contributed to an increased in IAEI. This result tells us that the joint effects of R&D expenditure and fixed assets investment were targeted toward an "output-increasing effect" instead of an "energy-saving effect". Such results are important since China's industrial sector is an investment-intensive sector. In this paper, both the sectoral energy intensity and the industrial structure contributed to decrease IAEI. Besides examining the industrial sector as a whole, we also explored the contributions of specific industrial sub-sectors through each driving factor. For most industrial sub-sectors, R&D efficiency, sectoral energy intensity and industrial structure contributed to a decrease in IAEI. Among them, the *ferrous metals* sub-sector (S_{25}) was the main contributor. For R&D intensity and investment intensity, the *non-metallic* sub-sector (S_{24}) was for the main contributor to an increase in IAEI. These results are important for policy-makers to provide policy recommendations related to investment targeted to particular industrial sub-sectors.

The results obtained can also be used to evaluate the effectiveness of current policies in the industrial sector. From the decomposition results, we find that current policies related to energy efficiency improvement and adjustment of industrial structure in industrial sector have been effective. Furthermore, the results of the attribution analysis can tell us which sub-sectors are adaptable and sensitive to the implemented policies. The program "Top-1000 Enterprises" targeted to industrial sub-sectors of *ferrous metals*, *chemical materials*, *non-metallic minerals*, *petroleum, coking and nuclear fuel processing*, *electricity and heat production and supply*, *non-ferrous metals*, *coal mining and washing*, *textiles*, and *paper products*. The "Ten Key Projects" aimed to several economic industries, such as building and transportation, and the industrial sector is one of the major components. The "Differential Electricity Pricing Policy" was directed at energy-intensive industries. These policies did not yield the expected results on the *petroleum, coking and nuclear fuel processing* and *non-metallic mineral products* sub-sectors, while the *chemical materials*, *ferrous metals* and *non-ferrous metals* sub-sectors did respond as expected to these policies. Policies related to the adjustment of industrial structure were aimed at encouraging the development of high-tech and emerging industries as well as limiting high-pollution and high energy-consuming industries. The sub-sectors of *petroleum, coking and nuclear fuel processing*, *ferrous metals* and *electricity, heat production and supply* significantly contributed to the evolution of industrial structure. Additionally, the effects of R&D efficiency, R&D intensity and investment intensity can provide a guidance for industry managers to conduct more appropriate activities of R&D and investment.

In general, the effects of R&D investments will have impacts on the industry scale or technology improvements after a long period, and sometimes their impacts are the cumulative effect of investments in R&D over the years. Therefore, the parameter R&D investment in the decomposition analysis just can tell us what happened from the mathematical perspective and cannot reflect the reality very well. In the future, we will find an appropriate way to explore the relationship between R&D investment and CO_2 emissions, where the lag of investment effect will be considered.

3.5. Conclusion and policy implications

In order to gain a better understanding of the changes in IAEI of China, this study used the extended LMDI method to investigate its driving forces. Then, we went a step further to explore the contribution of industrial sub-sectors to percent change of IAEI through each driving factor using attribution analysis. In addition, technological factors related to the industrial sector and its sub-sectors were also studied, including R&D expenditure and investment. The method in this paper can provide a new perspective for the extension of Kaya identity in decomposition analysis. Attribution analysis can allocate the causes of energy consumption or CO_2 emissions in an energy system to its components (sub-sectors or regions) to reveal the relationship between integral and local details. The main results and policy implications are as follows:

Rational use of R&D expenditure and investment should be encouraged. The technological factors related to R&D expenditure and investment had significant impacts on industrial aggregate energy intensity. Therefore, policy interventions should be encouraged. The results of this study show that even though in most sub-sectors the R&D efficiency factor contributed to a decrease in industrial aggregate energy intensity, the remaining sub-sectors (e.g., *gas production and supply* (S_{35})) should turn R&D expenditure into developing energy-saving technology. Meanwhile, most sub-sectors should improve their investment efficiency, especially the *chemical* (S_{19}) and *non-metallic* (S_{24}) sub-sectors, because their investment did not lead to a higher proportion of output. Additionally, the government may strengthen the fiscal policies on the regulation of industries' energy consumption, such as taxation and subsidies [66]. In view of the fact that carbon emissions in China are closely related to fossil fuel consumption, an emissions trading market can be used to regulate the extensive energy consumption. The market mechanism will affect the investment behaviors. For example, enterprises could shift investment to update equipment, such as energy saving, environmental protection, efficient equipment instead of simply expanding production. The environmental impact of production equipment should also be taken into consideration, when purchasing new equipment and developing new projects.

Energy efficiency should be promoted. Although most sub-sectors contributed to decrease IAEI through sectoral energy intensity, the energy efficiency of some sub-sectors (e.g., *plastic products* (S_{23}), *non-metallic mineral products* (S_{24})) could be improved. The government can improve the energy efficiency by encouraging the import of advanced technology. Additionally, with the increase of electricity consumption in the total amount of energy consumption, encouraging enterprises to update the electrical equipment will be a practical pathway to conserve energy. Finally, a ladder energy price system can be set up to regulate the energy consumption of companies through a market mechanism.

The adjustment of industrial structure is required. An unreasonable industrial structure imposes a variety of negative impacts on the energy consumption and environmental impacts. Therefore, restructuring industries is needed [67]. According to the results this study obtained, some industrial sub-sectors, such as *non-ferrous metals* (S_{26}), contribute to an increase in IAEI through industrial structure. Therefore, industrial structure should further be optimized. Recently, a large number of exports about ferrous metals, non-ferrous metals and non-metallic products lead to the expansion of their enterprise scales. The rapid development of the internet results in rapid update of electronic equipment, which increased the extensive development of the related industries. Therefore, in order to meet the market demand of these commodities and achieve the goal of energy saving, two alternative measures can be implemented. First, the high-tech and emerging alternative industries should be developed in technical support and innovation investment by government. Second, the government can also restrict the production of specific products by adjusting the energy and resource taxes.

References

[1] Liu Y, Zhou Y, Wu W. Assessing the impact of population, income and technology on energy consumption and industrial pollutant emissions in China. Applied Energy 2015; 155: 904-917.

[2] BP. China Overtakes USA as Top Energy Consumer as World Demand Grows Strongly, Says BP in 60th Year of Global Energy. 2011. URL: <http://www.bp.com/extendedgenericarticle.do?categoryId=2012968&contentId=7069439>.

[3] National Bureau of Statistics of China (NBSC). China Energy Statistical Yearbook. NBSC, Beijing, China Statistics 2004-2016.

[4] Yang M, Patiño-Echeverri D, Yang F, Williams E. Industrial energy efficiency in China: Achievements, challenges and opportunities. Energy Strategy Reviews 2015; 6: 20-29.

[5] Xu X, Zhao T, Liu N, Kang JD. Changes of energy-related GHG emissions in China: An empirical analysis from sectoral perspective. Applied Energy 2014; 132: 298-307.

[6] National Development and Reform Commission (NDRC). Strategic Plan for Industrial Efficiency [2006]. URL:<http://ghs.ndrc.gov.cn/15ghgy/t20060529_70793.htm>.

[7] National Development and Reform Commission (NDRC). Guidance Catalogue of Industrial Structure Adjustment 2005. NDRC directive [2005] 40. URL: <http://www.sdpc.gov.cn/zcfb/zcfbtz/tz2005/t20050403_65133.htm>.

[8] National Development and Reform Commission (NDRC). Guidance Catalogue of Industrial Structure Adjustment 2011. NDRC directive [2011] 9. URL: < http://www.sdpc.gov.cn/zcfb/zcfbl/201104/t20110426_408008.html>.

[9] Liu N, Ma ZJ, Kang JD. Changes in carbon intensity in China’s industrial sector: Decomposition and attribution analysis. Energy Policy 2015; 87: 28-38.

[10] The State Council. Strategic Action Plan for Energy Development (2014-2020). 2014. URL: <http://www.gov.cn/zhengce/content/2014-11/19/content_9222.htm >.

[11] Ang, BW, Choi KH. Decomposition of aggregate energy and gas emission intensities for industry: a refined Divisia index method. Energy 1997; 18: 59-73.

[12] Choi KH, Ang BW. Attribution of changes in Divisia real energy intensity index-An extension to index decomposition analysis. Energy Economics 2012; 34: 171-176.

[13] Shao S, Yang LL, Gan C, Gan CH, Cao JH, Geng Y, Guan DB. Using an extended LMDI model to explore techno-economic drivers of energy-related industrial CO_2, emission changes: A case study for Shanghai (China). Renewable & Sustainable Energy Reviews 2016; 55: 516-536.

[14] Zhao X, Zhang X, Shao S. Decoupling CO_2, Emissions and Industrial Growth in China over 1993-2013: The Role of Investment. Energy Economics 2016; 60: 275-292.

[15] Zhang X, Zhao X, Jiang Z, Shao S. How to achieve the 2030 CO_2 emission-reduction targets for China's industrial sector: Retrospective decomposition and prospective trajectories. Global Environmental Change 2017; 44: 83-97.

[16] International energy agency (IEA). CO_2 Emissions From Fuel Combustion Highlights. 2017. URL: <http://www.iea.org/topics/climatechange/>.

[17] Wang H, Ang BW, Su B. Assessing drivers of economy-wide energy use and emissions: IDA versus SDA. Energy Policy 2017; 107: 585-599.

[18] Ang BW. Decomposition analysis for policymaking in energy: which is the preferred method? Energy Policy 2004; 32(9): 1131-1139.

[19] Wang Q, Li R. Drivers for energy consumption: A comparative analysis of China and India. Renewable & Sustainable Energy Reviews 2016; 62: 954-962.

[20] Cruz L, Dias J. Energy and CO_2 intensity changes in the EU-27: Decomposition into explanatory effects. Sustainable Cities & Society 2016; 26: 486-495.

[21] Lima F, Nunes ML, Cunha J, Lucena AFP. Driving forces for aggregate energy consumption: A cross-country approach. Renewable & Sustainable Energy Reviews 2016; 68: 1033-1050.

[22] Hardt L, Owen A, Brockway P, Heun MK, Barrett J, Taylor PG, Foxon TJ. Understanding the drivers of energy reduction in the UK productive sectors: Efficiency or offshoring? Applied Energy 2018; 223: 124-133.

[23] Moreau V, Vuille F. Decoupling energy use and economic growth: Counter evidence from structural effects and embodied energy in trade. Applied Energy 2018; 215: 54-62.

[24] Mousavi B, Lopez NSA, Biona JBM, Chiu ASF, Blesl M. Driving forces of Iran's CO_2 emissions from energy consumption: An LMDI decomposition approach. Applied Energy 2017; 206: 804-814.

[25] Zhang M, Bai C, Zhou M. Decomposition analysis for assessing the progress in decoupling relationship between coal consumption and economic growth in China. Resources Conservation & Recycling 2018; 129: 454-462.

[26] Liu X, Zhou D, Zhou P, Wang QW. Factors Driving Energy Consumption in China: A Joint Decomposition Approach. Journal of Cleaner Production 2017; 172: 724-734.

[27] Ke J, Price L, Ohshita S, Fridlley D, Khanna NZ, Zhou N, Levine M. China's Industrial Energy Consumption Trends and Impacts of the Top-1000 Enterprises Energy-Saving Program and the Ten Key Energy-Saving Projects. Energy Policy 2012; 50: 562-569.

[28] Hasanbeigi A, Price L, Fino-Chen C, Lu HY, Ke J. Retrospective and prospective decomposition analysis of Chinese manufacturing energy use and policy implications. Energy Policy 2013; 63: 562-574.

[29] Wang J, Zhao T, Wang YN. How to achieve the 2020 and 2030 emissions targets of China: Evidence from high, mid and low energy-consumption industrial sub-sectors. Atmospheric Environment 2016; 145: 280-292.

[30] Wang M, Feng C. Understanding China's industrial CO_2 emissions: A comprehensive decomposition framework. Journal of Cleaner Production 2017; 166: 1335-1346.

[31] Zhou X, Zhang M, Zhou M, Zhou M. A comparative study on decoupling relationship and influence factors between China's regional economic development and industrial energy-related carbon emissions. Journal of Cleaner Production 2017; 142 (2): 783-800.

[32] Ren S, Fu X, Chen XH. Regional variation of energy-related industrial CO_2 emissions mitigation in China. China Economic Review 2012; 23(4): 1134-1145.

[33] Wang J, Hu MM, Rodrigues JFD. An empirical spatiotemporal decomposition analysis of carbon intensity in China's industrial sector. Journal of Cleaner Production 2018; 195: 133-144.

[34] Liu CL, Fan Y, Wu G, Wei YM. Using LMDI method to analyze the change of China's industrial CO_2 emissions from final fuel use: An empirical analysis. Energy Policy 2007; 35: 5892-5900.

[35] Zha D, Zhou D, Ding N. The contribution degree of sub-sectors to structure effect and intensity effects on industry energy intensity in China from 1993 to 2003. Renewable & Sustainable Energy Reviews 2009; 13: 895-902.

[36] Wu L, Huo H. Energy efficiency achievements in China's industrial and transport sectors: How do they rate? Energy Policy 2014; 73: 38-46

[37] Lin B, Tan R. Sustainable development of China's energy intensive industries: From the aspect of carbon dioxide emissions reduction. Renewable & Sustainable Energy Reviews 2017; 77: 386-394.

[38] Lin B, Long H. Emissions reduction in China's chemical industry-based on LMDI. Renewable & Sustainable Energy Reviews 2016; 53: 1348-1355

[39] Wang Y, Zhu Q, Geng Y. Trajectory and driving factors for GHG emissions in the Chinese cement industry. Journal of Cleaner Production 2013; 53: 252-260.

[40] Lin B, Moubarak M. Decomposition analysis: Change of carbon dioxide emissions in the Chinese textile industry. Renewable & Sustainable Energy Reviews 2013; 26(10): 389-396.

[41] Wang M, Feng C. Decomposing the change in energy consumption in China's nonferrous metal industry: An empirical analysis based on the LMDI method. Renewable & Sustainable Energy Reviews 2018; 82: 2652-2663.

[42] Zhang Q, Xu J, Hasanbeigi A, Zhang W, Lu HY, Arens M. Comprehensive assessment of energy conservation and CO_2 emissions mitigation in China's iron and steel industry based on dynamic material flows. Applied Energy 2018; 209: 251-265.

[43] Yang ZB, Shao S, Yang LL, Miao Z. Improvement pathway of energy consumption structure in China's industrial sector: From the perspective of directed technical change. Energy Economics 2018; 72: 166-176.

[44] González D, Martínez M. Changes in CO_2, emission intensities in the Mexican industry. Energy Policy 2012;51(4):149-163.

[45] González PF, Landajo M, Presno MJ. The Divisia real energy intensity indices: Evolution and attribution of percent changes in 20 European countries from 1995 to 2010. Energy 2013; 58: 340-349.

[46] González PF. Exploring energy efficiency in several European countries. An attribution analysis of the Divisia structural change index. Applied Energy 2015; 137: 364-374.

[47] Choi KH, Oh W. Extended Divisia index decomposition of changes in energy intensity: A case of Korean manufacturing industry. Energy Policy 2014; 65: 275-283.

[48] Kim YG, Yoo JY, Oh W. Driving forces of rapid CO_2 emissions growth: a case of Korea. Energy Policy 2015; 82: 144-155.

[49] Andrés L, Padilla E. Energy intensity in road freight transport of heavy goods vehicles in Spain. Energy Policy 2015; 85: 309-321.

[50] Wang J, Zhao T, Xu XS, Zhang X. Exploring the changes of energy-related carbon intensity in China: an extended Divisia index decomposition. Natural Hazards 2016; 83(1): 501-521.

[51] Wang J, Zhao T, Zhang X. Changes in carbon intensity of China’s energy-intensive industries: a combined decomposition and attribution analysis. Natural Hazards 2017; 88(3): 1655-1675.

[52] Liu N, Ma ZJ, Kang JD. A regional analysis of carbon intensities of electricity generation in China. Energy Economics 2017; 67: 268-277.

[53] Wang H, Ang BW, Zhou P. Decomposition aggregate CO_2 emission changes with heterogeneity: An extended production-theoretical approach. Energy Journal 2018; 39(1): 59-79.

[54] Fisher-Vanden K, Jefferson GH, Ma J, Xu J. Technology development and energy productivity in China. Energy Economics 2006; 28(5): 690-705.

[55] Jung TY, Park TS. Structural change of the manufacturing sector in Korea: measurement of real energy intensity and CO_2 emission. Mitigation and Adaptation Strategies for Global Change 2000; 5: 221-238.

[56] Liu N, Ang BW. Factors shaping aggregate energy intensity trend for industry: Energy intensity versus product mix. Energy Economics 2007; 29: 609-635.

[57] Yang ZB, Shao S, Yang LL, Liu JH. Differentiated effects of diversified technological sources on energy-saving technological progress: Empirical evidence from China’s industrial sectors. Renewable and Sustainable Energy Reviews 2017; 72: 1379-1388.

[58] Shao S, Huang T, Yang LL. Using latent variable approach to estimate China’s economy-wide energy rebound effect over 1954-2010. Energy Policy 2014; 72: 235-248.

[59] Li K, Zhang N, Liu Y. The energy rebound effects across China’s industrial sectors: An output distance function approach. Applied Energy 2016; 184: 1165-1175.

[60] Ang BW. LMDI decomposition approach: a guide for implementation. Energy Policy 2015;86: 233-238.

[61] National Bureau of Statistics of China (NBSC). Fixed asset investments and R&D investment by sector 2004-2016. URL: < http://data.stats.gov.cn/easyquery.htm?cn=C01>.

[62] National Bureau of Statistics of China (NBSC). China Statistical Yearbook. NBSC, Beijing, China Statistics 2004-2008.

[63] National Bureau of Statistics of China (NBSC). Growth rate of industrial value added by sector 2009-2016. URL: < http://data.stats.gov.cn/easyquery.htm?cn=A01>.

[64] Ministry of Industry and Information Technology of the People's Republic of China (MIIT). 2017. URL: <http://www.miit.gov.cn/n1146290/n1146397/c5540242/content.html>.

[65] Zhao XL, Ma CB, Hong DY. Why did China's energy intensity increase during 1998-2006: decomposition and policy analysis. Energy Policy 2010; 38: 1379-1388.

[66] Lu Z, Shao S. Impacts of government subsidies on pricing and performance level choice in Energy Performance Contracting: A two-step optimal decision model. Applied Energy 2016; 184: 1176-1183.

[67] Li N, Yang H, Wang LC, Huang XJ, Zeng CF, Wu H, Ma XX, Song XT, Wei YN. Optimization of industry structure based on water environmental carrying capacity under uncertainty of the Huai River Basin within Shandong Province, China. Journal of Cleaner Production 2016; 112(5): 4594-4604.

Appendix A

Table A1. Previous studies of the industrial sector using LMDI.

Research topic	Method	Drivers for decomposition	Reference	Sub-sectors
Industrial CO_2 emissions	LMDI	Emission coefficient, energy structure, energy intensity, industrial structure, IVA	Xu et al. [5]	No
Industrial carbon intensity	LMDI& Attribution	Emission coefficient, energy intensity, industrial structure	Liu et al. [9]	Yes
Industrial carbon emissions (Shanghai)	LMDI	Emission coefficient, energy structure, energy intensity, R&D efficiency, R&D intensity, Investment intensity, industrial structure, economic activity	Shao et al. [13]	No
Industrial carbon intensity	LMDI	Emission coefficient, energy intensity, process carbon intensity, R&D efficiency, R&D intensity, Investment intensity, industrial structure, economic activity	Zhang et al. [15]	No
Industrial energy consumption and intensity	LMDI	Production effect, Efficiency effect, Structural effect	Ke et al. [27]	No
Industrial energy consumption	LMDI	Production growth, intensity effect, structural effect	Hasanbeigi et al. [28]	No
Industrial CO_2 emissions	LMDI& Cointegration	Emission coefficient, Energy structure, Energy intensity, industrial structure, Economic output	Wang et al. [29]	Regroup
Industrial CO_2 emissions	LMDI&PDA	Energy structure, energy intensity, economic activity, energy efficiency, energy saving, technical efficiency, technology change	Wang and Feng [30]	No
Industrial CO_2 emissions	LMDI	Emission coefficient, Energy structure, Energy intensity, industrial structure, Economic output	Zhou et al. [31]	No
Industrial CO_2 emissions	LMDI	Emission coefficient, Energy structure, Energy intensity, industrial structure, Economic output	Ren et al. [32]	No
Industrial carbon intensity	LMDI	Emission coefficient, Energy structure, Energy intensity	Wang et al. [33]	No
Industrial CO_2 emissions	LMDI	Industrial structure, economic activity, emission coefficient, energy intensity, energy structure	Liu et al. [34]	Yes
Industrial energy intensity	LMDI	Structure effect, intensity effect	Zha et al. [35]	Yes
Industrial energy intensity	LMDI	Structure effect, economic efficiency, energy efficiency	Wu and Huo [36]	Yes

Table A2. Equations for LMDI decomposition analysis.

Effect	Single-period LMDI-II decomposition	Multi-period LMDI-II decomposition
Sectoral energy intensity effect	$SEI^{t-1,t} = exp\left(\sum_{i=1}^{N} w_i^{s-v} ln \frac{SEI_i^t}{SEI_i^{t-1}}\right)$	$SEI^{0,T} = \prod_{t=1}^{T} SEI^{t-1,t}$
R&D efficiency effect	$RE^{t-1,t} = exp\left(\sum_{i=1}^{N} w_i^{s-v} ln \frac{RE_i^t}{RE_i^{t-1}}\right)$	$RE^{0,T} = \prod_{t=1}^{T} RE^{t-1,t}$
R&D intensity effect	$RI^{t-1,t} = exp\left(\sum_{i=1}^{N} w_i^{s-v} ln \frac{RI_i^t}{RI_i^{t-1}}\right)$	$RI^{0,T} = \prod_{t=1}^{T} RI^{t-1,t}$
Investment intensity effect	$FI^{t-1,t} = exp\left(\sum_{i=1}^{N} w_i^{s-v} ln \frac{FI_i^t}{FI_i^{t-1}}\right)$	$FI^{0,T} = \prod_{t=1}^{T} FI^{t-1,t}$
Industrial structure effect	$IS^{t-1,t} = exp\left(\sum_{i=1}^{N} w_i^{s-v} ln \frac{IS_i^t}{IS_i^{t-1}}\right)$	$IS^{0,T} = \prod_{t=1}^{T} IS^{t-1,t}$

w_i^{s-v} can be calculated as: $w_i^{s-v} = \frac{L(E_i^t/E^t, E_i^{t-1}/E^{t-1})}{\sum_{i=1}^{N} L(E_i^t/E^t, E_i^{t-1}/E^{t-1})}$, and $L(x,y)$ can be calculated as: $L(x,y) = \frac{y-x}{ln(y)-ln(x)}$, $x \neq y$; if $x = y$, $L(x,y) = x$.

Table A3. Equations for multi-period attribution analysis.

Effect	Multi-period attribution analysis
Sectoral energy intensity effect	$SEI^{0,T}$-1 = $\sum_{i=1}^{N} E_{SEI,i}^{0,T} = \sum_{i=1}^{N} \sum_{t=1}^{T} SEI^{0,t-1} E_{SEI,i}^{t-1,t}$
R&D efficiency effect	$RE^{0,T}$-1 = $\sum_{i=1}^{N} E_{RE,i}^{0,T} = \sum_{i=1}^{N} \sum_{t=1}^{T} RE^{0,t-1} E_{RE,i}^{t-1,t}$
R&D intensity effect	$RI^{0,T}$-1 = $\sum_{i=1}^{N} E_{RI,i}^{0,T} = \sum_{i=1}^{N} \sum_{t=1}^{T} RI^{0,t-1} E_{RI,i}^{t-1,t}$
Investment intensity	$FI^{0,T}$-1 = $\sum_{i=1}^{N} E_{FI,i}^{0,T} = \sum_{i=1}^{N} \sum_{t=1}^{T} FI^{0,t-1} E_{FI,i}^{t-1,t}$
Industrial structure	$IS^{0,T}$-1 = $\sum_{i=1}^{N} E_{IS,i}^{0,T} = \sum_{i=1}^{N} \sum_{t=1}^{T} IS^{0,t-1} E_{IS,i}^{t-1,t}$

Table A4. Classification of China's industrial sector.

Number	Industrial sub-sectors	Number	Industrial sub-sectors
S_1	coal mining and washing industry	S_{19}	chemical materials industry
S_2	oil and gas extraction industry	S_{20}	pharmaceutical manufacturing industry
S_3	ferrous metals mining industry	S_{21}	chemical fiber industry
S_4	non-ferrous metals mining industry	S_{22}	rubber products industry
S_5	non-metallic mineral extraction and mining industry	S_{23}	plastic products industry
S_6	agro food processing industry	S_{24}	non-metallic mineral products industry
S_7	food manufacturing industry	S_{25}	ferrous metals industry
S_8	beverage manufacturing industry	S_{26}	non-ferrous metals industry
S_9	tobacco products industry	S_{27}	metal products industry
S_{10}	textile industry	S_{28}	general equipment manufacturing industry
S_{11}	textiles and clothing manufacturing industry	S_{29}	special equipment industry
S_{12}	leather, fur, and feather industry	S_{30}	transportation equipment industry
S_{13}	wood processing and wood products industry	S_{31}	electrical machinery and equipment industry
S_{14}	furniture manufacturing industry	S_{32}	communication and electronic equipment industry

S_{15}	paper products industry	S_{33}	instrumentation and culture-office machinery industry
S_{16}	printing and recording media industry	S_{34}	electricity and heat production and supply industry
S_{17}	stationery and sporting goods manufacturing industry	S_{35}	gas production and supply industry
S_{18}	petroleum, coking and nuclear fuel processing industry	S_{36}	water production and supply industry

Appendix B: Tabular presentation of results in Figures 3-7

The tables on the following pages provide the same results as in Figures 3-7 in the main text in tabular form. For the full name of each sub-sector see Table A4. Numbers give the % contribution of each industrial sub-sector to the sectoral energy intensity effect, R&D efficiency effect, R&D intensity effect, investment effect and industrial structure effect. The single-period attribution results are based on the single-period decomposition results. Correspondances:

- Figure 3 -> Table B1
- Figure 4 -> Table B2
- Figure 5 -> Table B3
- Figure 6 -> Table B4
- Figure 7 -> Table B5

Table B1. Single-period attribution results of sectoral energy intensity effect: Contribution of each sub-sector to the single-period energy intensity effect (%).

Sector	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
S_1	-1.12	0.10	0.03	-0.15	0.32	0.56	-0.43	-0.05	-0.05	-0.24	-0.61	-0.40
S_2	-0.56	0.12	0.07	0.04	0.38	-0.14	0.04	-0.05	-0.02	0.04	0.01	-0.05
S_3	0.13	0.09	-0.04	-0.05	0.11	-0.23	0.15	-0.12	-0.15	-0.09	-0.12	-0.24
S_4	0.00	0.02	-0.01	-0.05	-0.07	-0.08	0.00	0.04	-0.05	-0.05	-0.04	-0.07
S_5	0.04	0.01	0.02	-0.05	0.01	-0.07	-0.14	-0.03	0.00	-0.08	-0.04	-0.07
S_6	0.52	0.04	-0.05	0.14	0.07	-0.26	-0.34	-0.14	-0.09	-0.14	-0.05	-0.09
S_7	0.14	0.04	0.02	-0.10	0.01	-0.10	-0.17	-0.05	-0.09	-0.06	-0.08	-0.05
S_8	0.27	0.06	-0.03	-0.09	-0.04	-0.11	-0.23	-0.04	-0.03	-0.03	-0.08	-0.05
S_9	-0.06	0.01	-0.02	-0.02	-0.02	-0.01	-0.01	0.01	-0.02	-0.01	-0.01	-0.01
S_{10}	0.62	0.01	0.15	-0.22	-0.34	-0.31	-0.18	0.03	-0.28	-0.28	-0.35	-0.10
S_{11}	0.05	0.03	0.01	-0.01	-0.02	-0.04	-0.02	-0.03	0.03	-0.03	-0.03	-0.03
S_{12}	0.02	0.01	0.04	-0.02	-0.03	-0.02	-0.03	-0.02	0.07	-0.03	-0.03	-0.01
S_{13}	0.07	0.07	0.01	-0.07	-0.02	-0.06	-0.08	-0.04	-0.03	-0.08	-0.06	-0.09
S_{14}	-0.03	0.00	0.02	-0.01	0.00	-0.01	0.00	-0.01	-0.01	-0.01	0.03	0.00
S_{15}	0.24	0.04	-0.04	-0.26	0.03	-0.10	-0.35	-0.09	-0.21	-0.17	-0.15	-0.11
S_{16}	-0.04	-0.05	0.01	-0.01	-0.01	-0.01	0.00	-0.02	-0.01	-0.01	-0.01	-0.02
S_{17}	0.02	0.00	0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.02	0.00	-0.01	-0.02
S_{18}	1.85	0.45	1.02	-0.46	0.02	0.56	-0.67	0.29	-0.16	-0.21	-0.12	0.02
S_{19}	2.42	0.85	0.06	-1.55	-1.43	-1.61	-0.63	0.21	-0.61	-0.96	-0.60	-1.02
S_{20}	-0.02	0.04	0.00	-0.08	-0.03	-0.15	-0.05	-0.02	-0.04	-0.08	-0.09	-0.07
S_{21}	-0.05	-0.03	-0.11	-0.14	-0.23	-0.09	-0.05	0.03	-0.06	-0.07	-0.09	-0.03
S_{22}	0.06	0.11	0.03	-0.08	-0.06	-0.08	-0.03	-0.01	0.95	-0.09	-0.11	-0.14
S_{23}	0.21	0.17	0.01	-0.11	0.01	-0.09	-0.03	-0.10	13.12	-1.69	-1.25	-1.72
S_{24}	3.49	0.68	-1.18	-1.17	-0.03	-1.47	-1.02	0.54	11.91	-1.66	-2.60	-4.28
S_{25}	1.30	2.33	-0.76	0.72	0.81	1.18	-1.44	1.10	-22.28	-0.23	-0.24	0.73
S_{26}	0.06	0.16	-0.02	0.26	-1.13	-0.56	0.07	0.00	-4.20	0.00	-0.19	-0.25
S_{27}	0.09	0.07	0.08	-0.12	-0.03	-0.14	0.05	-0.21	-0.17	-0.16	-0.12	-0.17
S_{28}	0.07	0.11	0.02	-0.11	0.00	-0.14	-0.10	0.12	-1.07	-0.03	-0.03	-0.11
S_{29}	-0.03	0.00	-0.06	-0.11	-0.05	-0.08	0.00	-0.09	0.24	0.02	-0.04	-0.07
S_{30}	0.17	-0.12	-0.04	-0.21	-0.12	-0.10	0.07	-0.01	-1.06	-0.07	-0.10	-0.04
S_{31}	0.10	-0.04	0.07	-0.06	-0.03	-0.08	-0.01	-0.02	-0.06	-0.05	-0.10	-0.08
S_{32}	-0.01	-0.04	0.05	0.03	-0.01	-0.03	0.02	-0.07	-0.08	-0.07	-0.05	-0.06
S_{33}	-0.04	0.01	0.00	0.00	-0.01	0.00	0.01	-0.03	-0.01	-0.01	-0.02	-0.01
S_{34}	-1.04	-0.28	-0.02	-0.63	-0.43	-0.08	-0.07	0.46	-0.45	0.20	-0.37	0.07
S_{35}	-0.06	-0.05	-0.05	-0.06	-0.07	-0.04	-0.02	-0.02	0.01	0.01	-0.04	-0.01
S_{36}	0.07	0.01	0.01	0.01	0.01	0.01	0.03	0.01	0.02	0.00	0.00	-0.01
Total change (%)	8.95	5.03	-0.67	-4.80	-2.42	-3.96	-5.67	1.58	-4.93	-6.42	-7.80	-8.65

Table B2. Single-period attribution results of R&D efficiency effect: Contribution of each sub-sector to the single-period R&D efficiency effect (%).

Sector	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
S_1	-0.99	-0.13	-0.51	-0.23	-0.68	-0.93	-0.01	-0.26	-0.01	0.31	0.26	0.15
S_2	-0.79	-0.08	-0.14	-0.25	-0.59	-0.80	-0.45	0.19	-0.03	0.14	-0.02	0.46
S_3	-0.11	-0.09	0.11	-0.57	-0.34	0.26	-0.26	-0.05	-0.15	-0.04	0.00	0.04
S_4	0.14	0.07	-0.05	-0.34	0.09	-0.21	0.11	-0.22	-0.13	0.07	0.08	-0.01
S_5	0.28	-0.61	0.26	-0.18	0.02	0.14	-0.05	-0.33	0.02	0.09	-0.11	0.01
S_6	-0.08	-0.55	-0.49	-0.54	-0.31	-0.32	-0.20	-0.65	-0.34	-0.16	-0.04	-0.06
S_7	0.05	-0.11	-0.22	-0.12	0.03	-0.41	-0.05	-0.19	-0.14	-0.01	-0.02	-0.08
S_8	-0.19	-0.14	-0.08	-0.12	0.00	-0.08	-0.01	-0.10	-0.02	0.05	-0.04	0.08
S_9	-0.01	-0.06	0.05	-0.02	0.01	-0.03	0.00	0.00	-0.01	0.00	0.01	0.01
S_{10}	-1.03	-0.05	-0.21	-0.27	-0.10	-0.67	-0.28	-0.92	0.22	-0.05	-0.07	-0.28
S_{11}	0.05	-0.10	0.01	0.02	-0.03	-0.05	0.01	-0.12	-0.18	-0.05	0.00	-0.05
S_{12}	0.00	-0.03	-0.02	-0.07	0.01	-0.08	-0.02	-0.04	-0.10	-0.03	-0.02	-0.05
S_{13}	-0.04	-0.18	0.17	-0.11	0.07	0.12	0.06	-0.37	-0.07	-0.14	-0.04	-0.10
S_{14}	-0.14	0.01	-0.01	-0.02	0.02	-0.03	0.05	-0.06	-0.03	-0.03	-0.01	-0.02
S_{15}	0.07	-0.48	-0.32	0.08	-0.51	-0.34	0.01	-0.40	-0.33	-0.09	-0.01	-0.09
S_{16}	0.08	-0.03	0.01	-0.10	0.03	-0.07	-0.03	-0.07	-0.02	-0.02	0.00	0.00
S_{17}	-0.07	0.01	-0.02	-0.01	-0.02	-0.04	0.03	-0.04	-0.08	-0.03	-0.02	0.00
S_{18}	-3.11	-0.37	-3.02	0.11	-1.63	-1.07	-0.98	-1.30	-1.15	-0.15	-0.65	0.55
S_{19}	-3.41	-2.10	-0.55	-2.16	-0.81	-0.22	-1.23	-6.28	-0.88	-0.97	-0.06	0.31
S_{20}	0.13	-0.20	-0.14	-0.04	0.00	-0.11	-0.05	-0.23	-0.11	-0.05	0.01	-0.02
S_{21}	-0.23	-0.31	-0.31	-0.07	0.11	0.01	-0.09	-0.14	0.02	0.05	-0.01	0.01
S_{22}	-0.09	-0.08	-0.35	-0.06	0.04	-0.04	-0.13	-0.03	-0.94	-0.07	-0.04	0.00
S_{23}	-0.13	-0.07	-0.19	0.17	-0.35	-0.10	-0.14	-0.33	-3.52	-2.39	-0.40	-0.72
S_{24}	1.03	-3.14	-0.32	0.69	-3.78	-2.16	-1.83	-4.30	-26.49	2.83	2.88	5.80
S_{25}	-3.55	-3.90	-1.92	-3.95	-6.30	0.95	-4.54	-2.79	8.67	-0.07	0.04	-0.51
S_{26}	-0.82	-1.94	-0.96	-0.05	0.39	-0.28	-0.35	-1.55	0.35	-0.13	0.09	-0.03
S_{27}	-0.06	-0.64	-0.21	-0.30	-0.20	-0.02	-0.18	-0.53	-1.69	-0.03	0.00	0.09
S_{28}	0.02	-0.20	-0.37	-0.10	-0.09	-0.17	0.10	-0.51	0.02	-0.07	0.03	0.02
S_{29}	0.07	-0.23	-0.07	-0.09	-0.05	-0.16	0.00	-0.16	-0.28	-0.09	-0.07	-0.10
S_{30}	-0.27	-0.29	-0.09	0.01	0.08	-0.10	-0.06	-0.22	0.64	0.00	0.00	0.02
S_{31}	-0.02	-0.07	-0.19	-0.04	-0.02	-0.10	-0.08	-0.19	-0.03	-0.05	-0.01	-0.02
S_{32}	-0.06	0.00	-0.04	-0.04	-0.02	-0.12	-0.07	-0.13	-0.02	-0.05	0.01	-0.05
S_{33}	-0.03	-0.02	0.01	-0.04	-0.01	-0.03	0.00	-0.07	0.01	-0.01	0.00	0.00
S_{34}	1.02	0.30	-1.05	-0.27	-0.22	-0.59	0.11	-0.76	-0.25	-0.85	0.04	-1.42
S_{35}	0.13	0.23	-0.01	0.02	-0.07	0.16	-0.30	0.00	-0.06	-0.09	-0.05	0.00
S_{36}	-0.04	0.30	-0.05	-0.11	0.07	-0.10	-0.13	-0.10	-0.21	-0.05	-0.09	-0.08
Total change (%)	-12.2	-15.3	-11.3	-9.16	-15.2	-7.78	-11.1	-23.3	-27.34	-2.23	1.66	3.83

Table B3. Single-period attribution results of R&D intensity effect: Contribution of each sub-sector to the single-period R&D intensity effect (%).

Sector	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
S_1	0.46	-1.18	0.09	0.12	-0.01	0.40	-0.18	0.09	-0.02	0.06	0.20	0.23
S_2	0.75	-0.55	-0.37	-0.04	0.19	0.80	0.49	-0.16	0.05	-0.39	0.02	-0.22
S_3	-0.29	-0.25	-0.13	0.66	0.04	-0.29	0.25	0.12	0.18	0.12	0.11	0.15
S_4	-0.27	-0.26	-0.12	0.23	-0.11	0.16	-0.15	0.26	0.19	-0.07	-0.04	0.05
S_5	-0.53	0.24	-0.42	0.08	-0.18	-0.28	-0.08	0.40	-0.10	-0.10	0.10	0.01
S_6	-0.21	-0.02	0.24	0.20	0.15	-0.08	0.02	0.46	0.20	0.03	-0.04	0.04
S_7	-0.10	-0.13	0.01	0.06	-0.05	0.25	-0.03	0.20	0.07	-0.04	-0.03	0.03
S_8	0.13	-0.06	-0.21	0.07	0.00	-0.01	-0.05	0.04	-0.10	-0.13	0.02	-0.07
S_9	0.02	0.06	-0.07	0.04	-0.01	-0.01	0.02	-0.02	0.04	-0.01	0.00	0.01
S_{10}	0.86	-0.60	-0.11	0.19	0.65	0.39	-0.80	0.63	-0.22	-0.09	-0.01	0.09
S_{11}	-0.10	0.00	-0.10	-0.09	0.03	0.01	-0.11	0.07	0.22	0.00	-0.04	0.00
S_{12}	-0.01	-0.06	-0.05	0.07	-0.01	0.04	-0.01	0.02	0.06	-0.01	0.01	0.03
S_{13}	-0.05	0.03	-0.30	0.01	-0.07	-0.20	-0.13	0.37	0.01	0.10	0.01	0.05
S_{14}	0.14	-0.04	-0.01	0.01	-0.03	0.02	-0.07	0.06	0.02	0.02	-0.01	0.00
S_{15}	-0.35	0.19	0.16	-0.23	0.38	0.05	-0.05	0.28	0.32	-0.04	0.05	0.15
S_{16}	-0.13	-0.01	-0.04	0.10	-0.04	0.04	0.01	0.07	0.01	0.00	-0.02	-0.01
S_{17}	0.05	-0.06	-0.01	-0.02	0.03	0.03	-0.06	0.04	-0.01	0.02	0.01	-0.02
S_{18}	-1.36	-1.41	1.76	-1.33	0.69	1.09	1.01	1.55	1.15	-0.59	0.70	1.07
S_{19}	0.15	-1.17	-0.50	0.57	-1.07	-1.83	1.00	6.71	-1.50	0.26	0.45	0.51
S_{20}	-0.13	0.16	0.17	0.10	-0.05	-0.06	0.00	0.12	-0.01	-0.02	-0.02	0.01
S_{21}	-0.04	0.41	0.32	0.01	0.07	0.09	-0.25	-0.03	-0.04	-0.11	0.05	0.02
S_{22}	0.05	0.06	-0.03	0.07	0.01	-0.10	0.06	-0.07	1.11	-0.07	0.13	-0.05
S_{23}	0.04	-0.16	-0.03	-0.20	0.33	-0.07	0.00	0.25	3.71	1.15	-0.19	0.29
S_{24}	-4.43	1.23	-1.99	-3.76	0.62	-1.32	0.37	4.14	33.74	-3.47	-3.51	-5.35
S_{25}	1.53	2.46	6.67	4.47	2.69	0.23	7.10	-5.43	-10.37	0.68	0.94	1.56
S_{26}	0.65	1.34	0.99	-0.57	-0.73	-0.02	-0.42	1.18	-0.78	0.00	0.07	0.27
S_{27}	-0.34	0.08	-0.12	0.09	-0.03	-0.28	-0.13	0.50	2.29	-0.07	-0.08	-0.10
S_{28}	-0.33	-0.40	-0.02	-0.17	-0.13	-0.21	-0.25	0.82	-0.32	-0.02	-0.06	-0.03
S_{29}	-0.17	-0.04	-0.01	-0.05	-0.01	0.00	-0.11	0.11	0.07	0.01	0.02	0.06
S_{30}	-0.11	-0.14	0.04	-0.03	-0.15	-0.08	-0.07	0.11	-1.03	-0.03	0.01	-0.03
S_{31}	-0.22	-0.12	-0.02	-0.11	-0.11	-0.21	-0.16	0.01	0.08	0.04	0.00	0.01
S_{32}	0.03	0.02	-0.09	-0.07	0.01	0.07	-0.19	0.03	0.00	-0.03	0.00	0.02
S_{33}	0.02	0.01	-0.03	0.03	-0.02	0.01	-0.03	0.06	-0.03	0.01	0.01	0.00
S_{34}	-2.58	-1.39	1.04	0.86	0.67	-0.39	0.34	1.51	-0.13	0.47	-0.56	0.64
S_{35}	-0.18	-0.29	0.02	0.05	0.11	-0.24	0.29	-0.01	0.05	0.05	0.08	0.02
S_{36}	-0.05	-0.35	-0.03	0.04	-0.12	-0.10	0.15	0.16	0.21	-0.03	0.05	-0.01
Total change (%)	-7.10	-2.39	6.68	1.47	3.75	-2.10	7.77	14.66	29.12	-2.30	-1.58	-0.59

Table B4. Single-period attribution results of investment intensity effect: Contribution of each sub-sector to the single-period investment intensity effect (%).

Sector	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
S_1	0.63	1.47	0.47	0.13	0.79	0.59	0.19	0.22	0.03	-0.39	-0.46	-0.37
S_2	0.07	0.71	0.53	0.31	0.49	0.02	0.01	-0.08	-0.01	0.26	0.01	-0.22
S_3	0.47	0.40	0.02	-0.06	0.35	0.02	0.03	-0.06	0.02	-0.08	-0.11	-0.19
S_4	0.14	0.21	0.18	0.13	0.01	0.05	0.04	0.01	-0.01	0.00	-0.03	-0.03
S_5	0.27	0.45	0.14	0.11	0.16	0.15	0.14	0.01	0.07	0.01	0.01	-0.02
S_6	0.34	0.67	0.30	0.39	0.19	0.43	0.19	0.33	0.24	0.14	0.08	0.03
S_7	0.05	0.27	0.23	0.06	0.01	0.18	0.09	0.02	0.11	0.05	0.06	0.04
S_8	0.07	0.23	0.30	0.05	0.01	0.11	0.06	0.09	0.12	0.09	0.02	0.00
S_9	-0.01	0.01	0.02	-0.02	0.00	0.04	-0.02	0.02	-0.02	0.01	-0.01	-0.01
S_{10}	0.21	0.73	0.34	0.09	-0.56	0.32	1.09	0.48	-0.08	0.15	0.08	0.18
S_{11}	0.05	0.12	0.09	0.07	0.01	0.04	0.10	0.07	0.02	0.05	0.03	0.05
S_{12}	0.02	0.11	0.07	0.01	0.00	0.04	0.03	0.03	0.06	0.05	0.01	0.01
S_{13}	0.11	0.18	0.12	0.11	0.00	0.08	0.06	0.07	0.08	0.04	0.03	0.05
S_{14}	0.01	0.04	0.02	0.02	0.01	0.02	0.02	0.01	0.02	0.01	0.01	0.01
S_{15}	0.31	0.36	0.19	0.16	0.19	0.32	0.04	0.21	0.12	0.14	-0.04	-0.06
S_{16}	0.05	0.05	0.03	0.00	0.00	0.04	0.02	0.01	0.02	0.02	0.02	0.01
S_{17}	0.01	0.05	0.03	0.03	0.00	0.01	0.03	0.01	0.11	0.01	0.01	0.02
S_{18}	5.28	2.02	1.53	1.25	1.16	0.01	0.06	0.04	0.36	0.77	-0.06	-1.58
S_{19}	3.87	3.82	1.09	1.77	2.06	2.19	0.35	0.92	2.55	0.74	-0.40	-0.80
S_{20}	0.00	0.05	-0.02	-0.07	0.05	0.18	0.06	0.16	0.15	0.08	0.00	0.01
S_{21}	0.32	-0.09	0.03	0.06	-0.20	-0.10	0.35	0.20	0.01	0.06	-0.04	-0.03
S_{22}	0.05	0.03	0.41	-0.02	-0.05	0.15	0.08	0.11	0.13	0.14	-0.08	0.05
S_{23}	0.11	0.27	0.23	0.03	0.06	0.18	0.15	0.15	0.91	1.28	0.58	0.40
S_{24}	3.87	2.38	2.33	3.15	3.73	3.77	1.62	1.08	1.30	0.67	0.68	-0.32
S_{25}	2.44	1.91	-4.53	-0.32	4.47	-1.30	-2.07	8.85	-1.24	-0.64	-0.98	-1.05
S_{26}	0.22	0.81	0.06	0.65	0.31	0.33	0.79	0.70	0.30	0.13	-0.16	-0.23
S_{27}	0.47	0.68	0.35	0.24	0.26	0.31	0.32	0.15	-0.04	0.10	0.09	0.00
S_{28}	0.36	0.69	0.43	0.28	0.25	0.42	0.14	-0.19	0.27	0.09	0.04	0.02
S_{29}	0.11	0.32	0.09	0.16	0.06	0.18	0.11	0.09	0.29	0.09	0.05	0.04
S_{30}	0.44	0.50	0.06	0.02	0.06	0.20	0.14	0.16	0.17	0.03	-0.02	0.00
S_{31}	0.27	0.22	0.22	0.16	0.14	0.33	0.25	0.22	-0.04	0.01	0.01	0.01
S_{32}	0.04	-0.03	0.14	0.11	0.01	0.06	0.27	0.14	0.03	0.07	-0.01	0.03
S_{33}	0.01	0.01	0.02	0.01	0.03	0.03	0.03	0.02	0.01	-0.01	-0.01	0.00
S_{34}	1.75	1.20	0.11	-0.60	-0.45	1.06	-0.44	-0.58	0.43	0.40	0.53	0.74
S_{35}	0.04	0.04	-0.01	-0.08	-0.03	0.07	0.04	0.02	0.03	0.04	-0.03	-0.02
S_{36}	0.11	0.02	0.08	0.07	0.04	0.21	-0.01	-0.04	0.06	0.08	0.04	0.09
Total change (%)	22.59	20.93	5.69	8.48	13.63	10.76	4.33	13.65	6.59	4.68	-0.05	-3.11

Table B5. Single-period attribution results of industrial structure effect: Contribution of each sub-sector to the single-period industrial structure effect (%).

Sector	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
S_1	0.40	-0.23	-0.21	-0.04	-0.47	-0.05	0.01	0.08	-0.01	-0.03	-0.13	-0.15
S_2	-0.06	-0.32	-0.35	-0.26	-0.44	-0.05	-0.17	-0.12	-0.09	-0.10	-0.11	-0.08
S_3	-0.01	0.02	0.06	0.06	-0.12	0.09	0.02	0.05	0.08	0.07	0.03	0.01
S_4	0.04	-0.03	0.00	0.01	0.03	0.03	-0.01	0.00	0.03	0.02	-0.01	-0.01
S_5	-0.05	-0.07	-0.01	0.00	-0.04	0.05	0.03	0.04	0.00	0.00	0.00	-0.01
S_6	-0.08	0.04	-0.02	-0.13	-0.10	0.08	-0.02	-0.01	0.05	0.04	-0.02	-0.03
S_7	0.01	-0.01	-0.03	-0.01	-0.02	0.02	-0.01	0.02	0.01	0.01	-0.01	-0.01
S_8	-0.05	-0.04	-0.02	0.02	0.01	0.02	-0.01	0.02	0.01	0.01	0.00	-0.02
S_9	-0.02	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
S_{10}	-0.01	0.05	-0.18	-0.08	-0.02	-0.07	-0.14	-0.15	0.07	0.03	-0.05	-0.07
S_{11}	-0.01	-0.01	0.00	-0.01	-0.01	0.00	-0.01	0.00	-0.01	-0.01	-0.01	-0.01
S_{12}	0.00	-0.01	-0.01	-0.01	0.01	-0.01	0.00	0.00	0.00	-0.01	-0.01	-0.01
S_{13}	0.02	0.00	0.00	0.06	0.03	0.03	0.03	0.03	0.02	0.01	0.00	0.00
S_{14}	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
S_{15}	0.03	-0.01	-0.12	-0.04	-0.08	-0.01	-0.01	0.00	-0.02	-0.03	-0.03	-0.04
S_{16}	-0.01	-0.01	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00
S_{17}	0.00	0.00	0.00	-0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.01
S_{18}	-1.05	-1.13	-1.33	0.24	-0.61	-0.34	-0.36	-0.35	-0.27	-0.23	-0.25	-0.23
S_{19}	-0.38	-0.72	-0.44	0.72	-0.19	0.50	-0.14	0.01	0.21	0.13	0.17	0.11
S_{20}	0.00	-0.02	-0.03	0.00	0.00	0.03	-0.01	0.02	0.03	0.03	0.02	0.02
S_{21}	-0.07	-0.02	0.00	0.05	0.07	0.01	-0.04	-0.03	0.02	0.01	0.00	-0.01
S_{22}	0.00	-0.03	-0.07	0.02	0.01	0.01	0.00	-0.02	-0.11	-0.01	0.00	-0.01
S_{23}	-0.04	-0.04	0.02	-0.01	0.00	0.01	0.01	-0.01	-0.52	-0.08	-0.02	-0.11
S_{24}	-0.83	-0.52	-0.12	0.22	-0.59	0.44	0.37	0.46	0.24	0.11	0.15	-0.07
S_{25}	-0.39	1.27	0.71	-0.78	-3.14	-0.25	-1.28	-0.96	-0.06	-0.07	-0.05	-0.21
S_{26}	0.10	-0.02	0.40	0.01	0.77	0.09	-0.10	-0.04	0.09	0.04	0.06	0.04
S_{27}	-0.05	-0.04	0.02	0.04	-0.02	-0.02	0.02	0.03	0.03	0.02	0.02	0.02
S_{28}	0.04	0.02	-0.01	0.05	0.00	0.00	0.06	0.04	-0.02	-0.01	-0.01	0.00
S_{29}	0.02	0.01	0.06	0.04	0.03	0.01	0.02	0.03	-0.01	-0.02	-0.02	-0.03
S_{30}	-0.11	-0.07	0.04	0.16	0.12	0.09	0.06	-0.04	-0.04	-0.01	0.01	0.01
S_{31}	0.03	0.01	-0.03	0.01	0.04	0.01	0.01	0.00	0.00	-0.01	0.00	0.00
S_{32}	0.07	0.07	0.04	-0.07	-0.02	-0.05	0.00	0.01	0.02	0.01	0.00	0.03
S_{33}	0.00	0.00	0.01	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00
S_{34}	-0.09	-0.13	-0.24	0.09	0.18	-0.24	-0.22	-0.19	-0.28	-0.27	-0.22	-0.36
S_{35}	0.01	0.00	0.02	0.05	0.03	0.01	0.00	0.00	0.00	0.00	0.01	0.01
S_{36}	-0.05	-0.03	-0.03	-0.05	-0.02	-0.02	-0.04	-0.03	-0.02	-0.02	-0.02	-0.01
Total change (%)	-2.61	-2.06	-1.90	0.36	-4.58	0.39	-1.93	-1.12	-0.55	-0.38	-0.51	-1.21

Chapter 4

The impact of regional convergence in energy-intensive industries on China's CO_2 emissions and emission goals[6]

Abstract: In order to respond to climate change, China has committed to reduce national carbon intensity by 40-45% in 2020 and 60-65% in 2030, relative to 2005. Given that energy-intensive industries represent ~80% of total CO_2 emissions in China and that China is a large and diverse country, this paper aims to investigate the potential contribution of regional convergence in energy-intensive industries to CO_2 emissions reduction and to meeting China's emissions goals. To the best of our knowledge this matter has never been explored before. Using panel data from 2001 to 2015, we build three scenarios of future carbon intensities: business as usual (BAU), frontier (based on the directional distance function, in which all regions reach the efficiency frontier) and best available technology (BAT, in which all regions adopt the lowest-emitting technology). The frontier and BAT scenarios represent a weak and a strong form of regional convergence, respectively, and the BAU assumes that it develops following historical patterns. We then use the Kaya identity to estimate CO_2 emissions up to 2030 under the three scenarios. Our results are as follows: (1) Under BAU, the CO_2 emissions of energy-intensive industries increase from 7382.8 $MtCO_2$/yr in 2015 to 8127.6 $MtCO_2$/yr in 2030. Under the frontier scenario the emissions in 2030 are 44.23% lower than under business as usual, while under the BAT scenario this value becomes 84.81%. *Electricity* and *ferrous metals* are the sectors that most contribute to the reduction potential. (2) Even under BAU the carbon intensity of energy-intensive industries as a whole and all of its constituent sub-sectors except for *electricity* will decrease by more than the nationally-mandated averages. (3) Regional convergence could help the energy-intensive industries peak its CO_2 emissions before 2030, while under BAU the absolute emissions of the energy-intensive industries keep increasing.

Keywords: CO_2 emissions; Energy-intensive industries; Regional convergence; Scenario analysis.

4.1. Introduction

The Paris Agreement includes objectives to limit the global temperature increase above pre-industrial levels to well below 2°C and to pursue efforts to limit the increase to 1.5 °C. The most important pillars for achieving the goal of the Agreement is a rapid GHG (greenhouse gas) emission reduction (IEA, 2017). In this context, the Chinese government committed to achieve the emissions peak around 2030 or earlier, and reduce carbon intensity (CO_2 emissions per unit of GDP) by 40-45% in 2020 and 60-65% in 2030, compared to 2005. At the global level, the industrial sector is responsible for over a third of energy consumption and a slightly higher share of carbon emissions (Fais et al., 2016). This percentage is even higher in China since the Chinese model of development has relied

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heavily on the industrial sector, with energy-intensive industries supporting domestic infrastructure construction, heavy industries and the manufacturing of consumption goods for export (NBSC, 2016). In *Statistics Report on National Economic and Social Development in 2010*, Petroleum Processing and Coking Industry (*petroleum*), Raw Chemical Materials and Products Industry (*chemicals*), Non-metallic Mineral Products Industry (*non-metallic products*), Smelting and Pressing of Ferrous Metals industry (*ferrous metals*), Smelting and Pressing of Non-ferrous Metals industry (*non-ferrous metals*) and Production and Distribution of Electric and Heat industry (*electricity*) are classified as energy-intensive industries due to their higher energy consumption, where each of them is an energy-intensive sub-sector. These energy-intensive industries together generated 79.68% of China's CO_2 emissions in 2015 (Shan et al., 2018). Owing to the crucial role energy-intensive industries play in controlling CO_2 emissions in China, the government has issued special emission reduction policies and set energy consumption/intensity reduction targets for these sectors: during the 13th Five Year Plan (FYP) (2016-2020) the energy consumption in *ferrous metals* sector should decrease by at least 10% and the energy intensity (energy consumption per unit of GDP) in both *non-ferrous metals* and *petrochemicals* sectors should be reduced by 18%.

The decline in energy intensity has been identified as the most important factor contributing the historical decrease in carbon intensity (Fan et al., 2007; Zhang et al., 2010; Wang et al., 2017, 2018a). In turn, many studies found that technological progress is a crucial factor historically driving the improvement of energy intensity in China (Shao et al., 2014; Wang et al., 2018b). In other words, technology improvements have been recognized as the primary contributor to China's emission reduction over the past few years (Guan et al., 2014; Su and Ang, 2017). There are large heterogeneities in the carbon intensity (CO_2 emissions per unit of industrial value added) of energy-intensive industries across provinces varying from 0.059 Mt/billion yuan in Beijing to 1.21 Mt/billion yuan in Xinjiang in 2015 (2000 constant price), reflecting differences in resources endowments and development level. Considering the heterogeneity across provinces, it is meaningful to explore the impact of regional convergence on CO_2 emissions/intensity.

Economic convergence is the phenomenon whereby poorer countries (or regions) approach the income level of richer countries (or regions) (Sachs and Warner, 1995). According to Hao and Peng (2017) there is convergence within a country if interior regions are open and there is free mobility of factors such that the market and the law of diminishing returns will produce a self-correcting effect, with the result that per capita income and/or output levels in different regions tend towards equilibrium. In China, the relatively high degree of openness among provinces provides the prerequisite for regional convergence (Hao and Peng, 2017). As far as energy-intensive industries are considered, there are few technical barriers and a large scope for technological diffusion, see Bataille et al. (2018) for details of the technological features of these industries. Thus, regional convergence occurs through technological diffusion and adoption, leading to the production technology for a specific energy-intensive sub-sector in different provinces becoming similar (Ciscar and Soria, 2000; Alexiadis, 2011; Gries et al., 2018). One aspect of a production technology is its carbon intensity, and we expect there to be a catch-up effect, with lowest-performing regions improving in relative terms, when compared with the best performers, if indeed there is regional convergence. Of course, there might be good reasons, such as natural endowments or a long life-time of industrial installations, to prevent convergence in carbon intensities across regions.

In this paper we try to answer how regional convergence in each energy-intensive sub-sector could impact CO_2 emissions and contribute to meet China's 2020 and 2030 emissions targets. To the best of our knowledge this question has never been addressed before, although past studies have examined the likelihood that the 2020 and 2030 emission targets will be met considering other factors, and historical regional convergence in carbon emissions has been explored in China and elsewhere. We review these studies later in the paper.

This paper addresses the research question as follows. First, we establish three scenarios in terms of carbon intensity until 2030: a business-as-usual (BAU) scenario, in which the carbon intensity is the national average and develops following historical patterns; a frontier scenario, in which each province achieves the median carbon intensity of provinces on the efficiency frontier, as determined by the directional distance function (DDF); and a best available technology (BAT) scenario, in which the carbon intensity of each province approaches that of the province with the lowest carbon intensity. The BAU scenario represents a continuation of the current trend of regional convergence but in empirical terms historical convergence is negligible. The frontier and the BAT scenarios represent, respectively, a weak and strong form of regional convergence. Afterwards, these carbon intensity estimates are combined with estimates of sectoral growth to project absolute CO_2 emissions. Finally, by comparing the three scenarios, we can study the contribution of regional convergence in energy-intensive industries to emissions reduction and towards meeting China's emissions goals.

The remainder of this paper is organized as follows. Section 4.2 reviews the related literature. Section 4.3 introduces the methods and data set. Section 4.4 presents the results. Section 4.5 interprets and discusses those results. Section 4.6 concludes the paper and provides some policy implications.

4.2. Literature review

4.2.1 China's likelihood of meeting the 2020 and 2030 emissions goals

There are many studies exploring whether China could achieve the proposed emission reduction targets of 2020 and 2030, so for clarity we organize these materials in several groups. Some studies employed different methods to establish a relationship between CO_2 emissions and its major drivers, such as GDP, energy consumption, energy structure and population, in order to predict the CO_2 emissions. Zhu et al. (2015) considered the relationship between CO_2 emissions with energy consumption, economic development and energy structure to explore whether (or not) China can realize the carbon intensity targets. Zhu et al. (2018) set different scenarios based on the growth rates of population, GDP per capita and energy structure to investigate the path choice of achieving China's 2020 intensity targets. Using econometric analysis, Xu et al. (2017) predicted the energy consumption based on the estimates of GDP and population, and then calculated the carbon emissions. Cansino et al. (2015) combined the I-O (input-output) analysis with econometric analysis to check the extent to which the commitment of China to carbon intensity reduction by 2020 will be fulfilled. These studies obtained the consistent results that the 2020 and 2030 reduction targets of carbon intensity can be achieved with ongoing policies. On the contrary, Elzen et al. (2016) and Yuan et al. (2012) pointed out that the peak of CO_2 emissions in 2030 and 40-45% reduction in carbon intensity by 2020 might not be achieved with the policies that are currently implemented.

Additionally, some papers just focused on the contribution of a single driver to the emissions targets. Considering the impact of energy structure on CO_2 emissions, Li et al. (2012) proved that the low carbon energy will contribute 9.74-24.42% to the 2020 carbon intensity target in the different scenarios. Liu et al. (2015) used a system dynamic model to identify the impact of renewable energy on carbon intensity, pointing out that carbon intensity will be reduced by 47-50% with the renewable energy policies. Niu et al. (2016) combined a unitary regression model, the compound growth model and the gray model together to examine the relationship between energy system transformation and emissions peak. The results suggested that with actively creating the conditions for transforming the energy system, China will achieve peak emissions by 2035. Focusing on the impact of economic growth on the emissions targets, Li and Lin (2016) used co-integration relationship to find a moderate range of the economic growth rate for achieving the 2020 emissions goal, showing that the economic growth rate should be between 7% and 8.4%. However, Mi et al. (2017) employed the Integrated Model of Economy and Climate (IMEC) and an optimized I-O model to assess the tradeoff between emission reduction and economic growth, and the results showed that carbon emissions will peak in 2026 if the annual GDP growth rate is less than 4.5%. Using the gray model, Li et al. (2018) suggested that China will achieve the emissions peak if the GDP was no more than 151,426.15 billion yuan by 2030. Regarding to the impact of shifts in industrial structure on the emissions targets, using multi-objective optimization Yu et al. (2018) found that emissions cannot reach the peak before 2030 if the industry structure (shares of agriculture, industry, service) develops as usual. Zhang et al. (2018) used dynamic factorization model to study the contribution of industrial structure to the reduction of CO_2 emissions up to 2030, showing that emission reduction caused by the shifts in industrial structure in three major industries (agriculture, industry and service) and in the industrial sub-sectors accounted for 28.22% and 4.26% of the national total emissions, respectively. Yang et al. (2018) studied the impact of industrial structure on the CO_2 emissions of Shanghai, suggesting that in order to achieve the emissions goal Shanghai should reduce the share of industrial sector in GDP from 49.4% in 2012 to 38.3% in 2020. Besides, Yi et al. (2011) employed emissions allocation model to explore how to allocate the CO_2 reduction target regionally to meet the national reduction target, suggesting that in order to achieve the 2020 target the provinces of Shanghai, Hebei, Shanxi, Shandong, Guangdong and Liaoning should reduce their carbon intensities by more than 45%. Cui et al. (2014) examined the impact of ETS (emissions trading system) on achieving China's 2020 reduction targets using the CGE (Computable General Equilibrium) model, finding that the partial ETS and the national ETS may result in the total abatement costs by 4.5% and 23.67% compared with the scenario of no ETS, respectively.

Different models have been used to forecast the CO_2 emissions/intensity of specific economic sectors. For instance, using the bottom-up model, Xiao et al. (2014) assessed the carbon abatement potential of building sector; Zheng et al. (2015) evaluated vehicle GHG emission trends of road transportation sector; and Hao et al. (2015) studied the possible trajectories of GHG emissions from China's freight transport sector. Based on the Kaya identity and scenario analysis, Zhou et al. (2016b) studied the future CO_2 emissions of China's civil aviation industry, showing that the CO_2 emissions will increase until 2020 and the carbon intensity cannot achieve the 2020 target with current mitigation measures. Within the industrial sector, combining LMDI (logarithmic mean Divisia index) method and co-integration technique, Wang et al. (2016) found that the industrial sector can achieve the 2020 and 2030 targets for carbon intensity even with the existing policies while the peak of CO_2 emissions cannot be realized before 2030. Combining the GM (1,1) and econometric models, Liu et al. (2014) drew the conclusion that the carbon intensity of thermal power sector in 2020 will be twice that of 2005. Zhou et al. (2018) used global change assessment model to explore CO_2 emissions of China's industrial sector up to 2050, indicating that CO_2 emissions will peak in 2025 with the policies for adjusting industrial structure, promoting low-carbon energy and capping energy and coal use. By using the Long-range Energy Alternatives Planning (LEAP) model, Wu and Peng (2016) estimated the CO_2 emissions and carbon intensity of *electricity* sector till 2030, indicating that the peak of emissions and the carbon intensity targets cannot be achieved; Wang et al. (2007) proved that the CO_2 emissions of *ferrous metals* sector can peak in 2020, while the carbon intensity targets both in 2020 and 2030 were far from being realized. Additionally, the Kaya identity, as a famous equation used to develop identical equation for driving forces, also has been used in industrial sector/sub-sectors. For instance, Zhang et al. (2017) obtained the partial similar results with Wang et al. (2016). They pointed out that the targets for carbon intensity in 2020 and 2030 can be achieved and industrial emissions will peak in 2025 with current policies. Xie et al. (2016) proved that the peak of CO_2 emissions from *petroleum* sector cannot be reached while the carbon intensity targets can be achieved.

4.2.2 Convergence in carbon and energy intensity

The phenomenon of convergence between countries and regions is receiving increasing attention in studies of energy consumption, CO_2 emissions and environmental quality. Zhu et al. (2014) studied the rate of carbon intensity reduction across 89 countries from 1980 to 2008, and found no convergence in carbon intensity. Mishra and Smyth (2017) studied whether convergence occurred in the energy consumption per capita of seven sectors in Australia for the period of 1973-2014 and the results indicated that there was convergence in energy consumption per capita for six of seven sectors. Kounetas (2018) studied the energy consumption and CO_2 emissions as well as their intensities in 23 European countries from 1970 to 2010, and found that there was no convergence. Han et al. (2018) explored the process of energy efficiency convergence among 89 countries from 2000 to 2014, showing that the efficiency gaps became larger after 2010. Yan et al. (2017) explored the development trend of low-carbon technologies in 72 countries from 1990 to 2012 and 19 OECD economies from 1960 to 2012. Their results showed that convergence patterns of low-carbon technologies did not occur across the 72 countries while it existed among the 19 OECD countries.

Concerning China in particular, the convergence of energy consumption, CO_2 emissions and carbon intensity has been studied recently. At the provincial level, Zhao et al. (2015) investigated the convergence of carbon intensity among China's 30 provinces over the period of 1990-2010, indicating that the carbon intensities are converging across provinces. Hao and Peng (2017) investigated the convergence of energy consumption per capita from 1994 to 2014, indicating that there was convergence across 30 provinces. Other studies do have the city perspectives. Zhou et al. (2016a) assessed the catch-up effect and convergence of energy use and CO_2 emissions across 214 cities from 2003 to 2009, indicating that the industrial energy conservation and emission reduction exhibited a trend of convergence across these cities during the study period. Wu et al. (2016) investigated the convergence of CO_2 emissions per capita among 286 cities during the period of 2002-2011. The results showed that CO_2 emissions per capita tended to converge. Focusing the six economic sectors (agriculture, industry, construction, transportation, service and residential sectors), Wang and Zhang (2014) examined the convergence of CO_2 emissions per capita in each sector across 28 provinces in China from 1996 to 2010, showing that the CO_2 emissions per capita in all sectors converged across provinces during the study period.

We now can identify the knowledge gap that motivates the present study. First, although there are many studies used different models to study China's emissions goals from different perspectives, most of them considered the contribution of macroeconomic factors to the emissions goals for China as a whole or specific regions or industries but do not pay attention to regional heterogeneities. However, focusing on specific industries at the regional level may be more relevant for policy-makers, especially if we focus on energy-intensive industries, since they play an important role in emission reduction. Second, convergence on energy consumption and CO_2 emissions in China has been studied, but all of these studies only identified whether there was historical convergence of CO_2 emissions/energy consumption across regions (Zhao et al., 2015; Hao and Peng, 2017; Zhou et al., 2016a; Wu et al., 2016; Wang and Zhang, 2014). To the best of our knowledge the potential impact of regional convergence on CO_2 emissions and its contribution to China's emissions goals have never been explored. To fill in the above-mentioned knowledge gaps, this study will explore this issue regarding to energy-intensive industries. We will use the Kaya identity and scenario analysis as methods to address the research question, as described in the following section.

4.3. Methods and data sources

4.3.1 General approach to the construction of sectoral CO_2 emission projections

The Kaya identity expresses CO_2 emissions as a product of several factors and has been widely used as a statistical forecasting model for CO_2 emissions projection (Friedlingstein et al., 2014; Zhu et al., 2015; Niu et al., 2016; Raftery et al., 2017; Zheng et al., 2018). In the identity, GDP per capita and population are usually considered as two key socioeconomic driving forces for CO_2 emissions, which next to (developments in) the CO_2 emission intensity per unit of GDP determine the total future CO_2 emissions. In this paper population will not be included as a driver. First, as stated by Zheng et al. (2018), the population size in the short-term is essentially constant. Furthermore, good projections of GDP are available for China, so that using a split between growth in GDP per capita and population growth is not needed. Finally, the focus of this paper is not the whole economy but specifically a specific set of energy-intensive industries. Energy-intensive sub-sectors like electricity production, ferrous metals production and chemicals production have very different CO_2 emission intensities per unit of output. In this paper, we therefore use the following formula to make projections of the industrial CO_2 emissions in China from 2016 to 2030, allowing for the use of sub-sector specific changes in CO_2 emission intensities and sub-sector specific output growth rates as a function of GDP growth:

$$[CO_2]_{t,i} = \left[\frac{CO_2}{OUT}\right]_{t,i} \times \left[\frac{OUT}{TOT}\right]_{t,i} \times \left[\frac{TOT}{GDP}\right]_t \times GDP_t \tag{1}$$

$$\left[\frac{CO_2}{OUT}\right]_{t,i} = \left[\frac{CO_2}{OUT}\right]_{t-1,i} \times (1 + g_{1i}) \tag{2}$$

$$\left[\frac{OUT}{TOT}\right]_{t,i} = \left[\frac{OUT}{TOT}\right]_{t-1,i} \times (1 + g_{2i}) \tag{3}$$

$$\left[\frac{TOT}{GDP}\right]_t = \left[\frac{TOT}{GDP}\right]_{t-1} \times (1 + g_3) \tag{4}$$

In the preceding expressions, $[CO_2]_{t,i}$ is the CO_2 emissions in sub-sector *i* in year *t*, with unit of Mt (Million tons) CO_2/yr, expressed as the product of four terms: $\left[\frac{CO_2}{OUT}\right]_{t,i}$ is the output-based carbon intensity of sub-sector *i* in year *t* (the ratio of carbon emissions to gross output in each energy-intensive sub-sector), measured in Mt CO_2/billion yuan; $\left[\frac{OUT}{TOT}\right]_{t,i}$ stands for the share of energy-intensive sub-sector *i* in the energy-intensive industries as a whole in year t (unit: billion yuan of gross output of sub-sector *i*/billion yuan of gross output of energy intensive industries as a whole); $\left[\frac{TOT}{GDP}\right]_{t}$ is the share of gross output of the energy-intensive industries in GDP in year t (unit: billion yuan/billion yuan): and GDP_t stands for the national GDP (billion yuan/yr) in China in year t.

From one year to another each of the three terms, output-based carbon intensity, the share of each specific sector, and the share of the energy-intensive industries in GDP, is assumed to grow (or decline) at a constant rate g_{1i}, g_{2i} and g_3, respectively. As will be elaborated in the section on data collection (4.3.5), historical data for all variables in equation (1) are available from a variety of statistical sources. Future growth rates of GDP data are readily available from the World Bank (World Bank, 2017), so the crux of this study is to create estimates for g_{1i}, g_{2i} and g_3. The share of each energy-intensive sub-sector (g_{2i}) and the share of energy-intensive industries (g_3) showed a rather steady development from 2006 to 2015, and we assumed that the average changes observed during this time period will continue into the future. We refer to Tables A1-2 in the Supplementary information. For assessing potential changes in sub-sector-specific carbon intensities (g_{1i}) a more sophisticated approach was used. Using observed differences in sub-sector specific carbon intensities between provinces, various scenarios for regional convergence of such carbon intensities were derived. Further (similar to the approach for g_{2i} and g_3) trends for historical changes sector-specific carbon intensities were extrapolated into the future. These scenarios and extrapolations will be elaborated in more detail in the next section.

After calculating the gross output of each energy-intensive sub-sector ($[OUT]_i$) and the total gross output of energy-intensive industries ($[TOT]$) from 2016 to 2030 based on g_{2i} and g_3, we corrected $[OUT]_i$, to ensure that the sum of output shares of energy-intensive sub-sectors in total output of energy-intensive industries will be equal to 100%. The initial estimate of $[OUT]_i$ for any given year obtained by extrapolation from the preceding year was multiplied by a correction factor, defined as the ratio of $[TOT]$ in that year divided by the sum of all initial estimates of $[OUT]_i$ in that year.

When performing provincial-level calculations, we use gross output as the metric of economic activity to predict CO_2 emissions (eq. (1) above), due to the absence of information concerning industrial value added (IVA) at the provincial level for each energy-intensive sub-sector. However, the emissions goals contained in Chinese environmental policies are framed using IVA as metric of economic activity and at the national level information on both gross output and IVA is available, thus allowing for the conversion between the two metrics. Because in the Results' section we will only present values of carbon intensity for the country as a whole rather than for specific provinces, the metric of carbon intensity used there will be defined as CO_2 emissions per unit of IVA (Mt/billion yuan).

4.3.2 Scenarios for sub-sector specific emission intensities based on provincial differences

Scenario analysis can help us to better understand the possible evolution of CO_2 emissions and carbon intensity in the future, as well as the impact of regional convergence on CO_2 emissions for a specific energy-intensive sub-sector. In this paper the different assumptions on the future carbon intensity reflect the different levels of regional convergence. Three scenarios will be considered, materialized in different values of the parameter of output-based carbon intensity, $\left[\frac{CO_2}{OUT}\right]_{t,i}$: business as usual (BAU), frontier and best available technology (BAT). The framework of scenario design is shown in Fig. 1 and the detailed description is as follows:

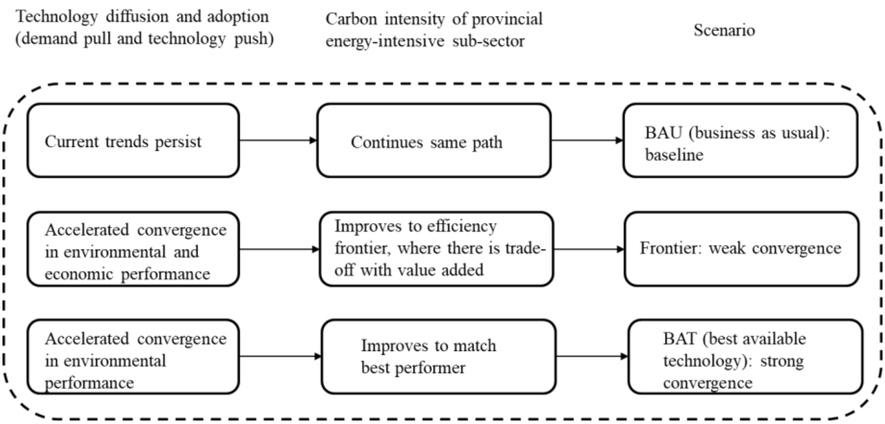

Fig. 1. The framework of scenario design.

(1) Under the BAU scenario, the point of departure is the average carbon intensity of a specific energy-intensive sub-sector at the national level, which can be calculated as the total CO_2 emissions over gross output of a specific energy-intensive sub-sector. For each sub-sector, historical changes in carbon intensity between 2006 and 2015 are assumed to continue until 2030. Implicitly, this scenario assumes that any underlying historical trends in regional convergence will persist into the future.

(2) Under the Frontier scenario, it is assumed that sub-sectors in different provinces converge with regard to the efficiency of the use of factor inputs in relation to desirable (production) output and undesirable (emission) output, in our case CO_2 emissions. The Frontier scenario differs from the BAT scenario below, in the sense that BAT minimizes the carbon intensity of output without considering any trade-off between environmental and economic performance. Particularly the large dependence of developing provinces on energy-inefficient production technologies offers considerable potential to reduce CO_2 emissions. Methods for estimating this potential have thus far focused on benchmarking the carbon intensities in all provinces with the most efficient one (Ward et al., 2017). We apply a specific type of Data Envelop Analysis (DEA) with the Directional Distance Function (DDF) to identify the gaps of technical efficiency across provinces, and calculate a benchmark reflecting an optimal balance between factor inputs, production output and CO_2 emissions. For each energy-intensive sub-sector, we perform a DDF. Under the DDF model (explained in more detail in the following subsection), each of the 30 provinces is interpreted as a decision-making unit, and we perform the ranking of provinces according to their technical efficiency (see Tables A3-8 of SI). We then select the provinces on the frontier and define the median value of their output-based carbon intensity as the frontier scenario. Thus, this scenario corresponds to a weak form of regional convergence, in which different provinces do not necessarily converge to a common single carbon intensity value, but to a range of values that reflect each province's particular trade-off between carbon emissions and economic output.

(3) In order to construct the BAT scenario, we analyzed all provincial output-based carbon emissions (for every sub-sector) and identified in which one the output-based carbon intensity is the lowest. Under this scenario it is assumed that, for a specific energy-intensive sub-sector, the performance of all provinces converges to the best-performing province. For the period up to 2030, it is assumed that the historical improvement rates of the carbon intensity of the best performing province (which may differ from year to year) will continue. Thus, this scenario corresponds to a strong form of regional convergence in carbon intensity. This scenario is less realistic than the preceding ones, particularly with regard to the assumption that BAT performance can be achieved in all sub-sectors across all provinces overnight. But even if one would allow for a reasonable time frame for diffusion of BAT, there might be practical constraints preventing the homogenization of carbon intensities. For example, even if the physical production technology is the same in different provinces the value added per unit of physical output might differ due to the distance between the production unit and the market it is serving. As another example, there might resource endowments that make it impractical to use the same physical production technology in different provinces (e.g., hydropower for electricity generation).

The regional convergence for each energy-intensive sub-sector in frontier and BAT scenarios can be achieved by technology diffusion and adoption. The rates of introduction and diffusion of new technologies from developed provinces to developing provinces will be driven by both demand-pull and technology-push forces (Costantini et al., 2015). Demand-pull approaches rely more on market incentives while technology-push approaches are often dependent on the knowledge stock and technological capacities acquired through research and development (R&D) activities (Costantini et al., 2015). Previous studies have shown that demand-pull approaches seem to benefit mature technologies, whereas technology-push approaches turn out to be necessary in stimulating innovation activities in less-mature technologies (Costantini et al., 2017). In this paper, we tend to focus on the diffusion of existing technologies from benchmarking provinces to other provinces even though new technology may emerge in the process. Therefore, the demand-pull policies are more important for guiding the regional convergence.

4.3.3 Constructing the Frontier scenario using the radial Directional Distance Function (DDF)

The DDF is a popular way for modeling energy and environmental issues and has attracted much attention due to the advantage of modeling good and bad outputs simultaneously. The DDF efficiency measure is a metric that represents the distance between the current performance of a decision-making unit (DMU) and its optimal performance, constrained by the observed performance of all DMUs, when the DMU is simultaneously allowed to expand desirable outputs and reduce inputs and/or undesirable outputs (Zhou et al., 2008).

Assume that the DMUs use input vector *x* to jointly produce desirable output vector *y* and undesirable output vector *b*. The multi-output production technology can be expressed as follows:

$$P(x)=\{(x, y, b): x\ can\ produce\ (y, b)\} \tag{5}$$

where $P(x)$ is required to satisfy the standard axioms of production theory (details see Färe et al., 2007). Additionally, in order to specify the environmental technology, weak disposability and null-jointness assumptions should be imposed on $P(x)$. The weak disposability and null-jointness assumption can be expressed respectively as follows:

(1) If $(x, y, b) \in P(x)$ and $0 \leq \theta \leq 1, then\ (x, \theta y, \theta b) \in P(x)$ and

(2) If $(x, y, b) \in P(x)$ and b=0, then y=0.

In order to expand desirable outputs and contract undesirable outputs simultaneously, the directional output distance function is introduced. Let $d = (d_y, d_b)$. Since the radial efficiency measure of the DDF has been identified to be effective when measuring technical efficiency (Zhang and Choi, 2014), the radial DDF proposed by Färe et al. (2007) is selected. We define the directional output distance function as $\overrightarrow{D_0}(x, y, b; d_y, d_b) = max\,\{\beta: (y + \beta d_y, b - \beta d_b) \in P(x)\}$. In general, there are two common ways to estimate the DDF: the parametric approach and non-parametric DEA approach. The DEA approach is a good choice if the research focus is measuring technical efficiency while the parametric method is usually used to estimate the shadow prices of pollutants (Zhang and Choi, 2014). Since this paper focuses on the technical efficiency, the following DEA-type model is used to compute the technical efficiency of k-th DMU for each energy-intensive sub-sector:

$$\overrightarrow{D_0}(x_k, y_k, b_k; d_y, d_b) = Max\ \beta_k$$
$$\begin{cases} \sum_{j=1}^{J} x_{mj}\lambda_j \leq x_{mk} & (m = 1, \dots, M) \quad (C1) \\ \sum_{j=1}^{J} y_{rj}\lambda_j \geq y_{rk} + \beta_k y_{rk} & (r = 1, \dots, R) \quad (C2) \\ \sum_{j=1}^{J} b_{fj}\lambda_j = b_{fk} - \beta_k b_{fk} & (f = 1, \dots, F) \quad (C3) \\ \sum_{j=1}^{J} \lambda_j = 1 & (j = 1, \dots, J) \quad (C4) \end{cases} \tag{6}$$
$$\lambda_j \geq 0 (j = 1, \dots, J), 1 \geq \beta_k \geq 0$$

where x_{mj}, g_{rj}, b_{fj} denote the m-th input, the r-th desirable output and the f-th undesirable output of the j-th DMU, respectively. λ_j are the intensity variables, representing weights assigned to DMU j when constructing the production possibilities frontier. J, M, R, and F are the numbers of DMUs, inputs, desirable outputs and undesirable outputs. β_k stands for the feasible expansion of DMU k. The objective function "maximum β_k" means the maximum proportion of desirable outputs expansion and the undesirable outputs contraction for DMU k. In this study, the desirable output is gross output (billion yuan/yr) and the undesirable output is CO_2 emissions ($MtCO_2$/yr). According to Yang and Pollitt (2010), the assumption of weak disposability is appropriate to model CO_2 emissions since CO_2 emissions cannot be directly reduced using existing technology like other pollutants. Therefore, in this study, the weak disposability assumption is used, which can be reflected by constraint (C3). The input vector x contains three indicators: the capital stock (billion yuan/yr), labor (10^4 people/yr) and energy consumption (million tons coal equivalent/yr); the desirable output vector y contains one indicator, gross output (billion yuan/yr); and the undesirable output vector b contains one indicator, CO_2 emissions ($MtCO_2$/yr). The sources of data set are explained in section 4.3.5.

The efficiency of DMU k can be obtained by the following equation:

$$\textit{Technical Efficiency} = 1 - \beta_k \tag{7}$$

If β_k equals to zero, DMU k is technically efficient, i.e., it is located at the frontier. However, a positive β_k indicates the extent of inefficiency of DMU k. Conceptually, DMU k has the potential to expand its gross output and reduce its CO_2 emissions by a factor of β_k until it reaches the technical frontier. Mathematically, if the original CO_2 emissions of DMU k are b_k, then its frontier emissions are $(1-\beta_k)b_k$; if its original gross output is y_k, then its frontier gross output is $(1+\beta_k)y_k$.

As stated in section 4.3.2, the DDF method is used in this paper to construct the frontier scenario. We choose the provinces whose efficiency equal to 1 (they are on the technical frontier), and then select the median output-based carbon intensity of these provinces. Under the frontier scenario the output-based carbon intensity of China as a whole is assumed to match median output-based carbon intensity of the efficiency frontier. This assumption reflects the idea that individual provinces have moved to the efficiency frontier, exhibiting regional convergence in economic and environmental performance.

4.3.4 Uncertainty analysis

The model to predict future CO_2 emissions described above (equations (1), (2), (3) and (4)) is deterministic, and yet there are uncertainties in the estimation of the yearly growth rates g_{1i}, g_{2i} and g_3 driving the model. To estimate the uncertainty of the results we perform a Monte Carlo analysis, considered as one of the most comprehensive and flexible techniques for analyzing problems that involve various uncertainties, as recommended by the IPCC (Zhang et al., 2017). In the Monte Carlo analysis we model g_{1i}, g_{2i} and g_3 as normally distributed random variables, independently sampled in each consecutive year from 2016 to 2030. We conduct this simulation 100 thousand times and use the resulting data to estimate the 90% and 50% inter-quantile widths of CO_2 emissions from 2016 to 2030 and thus assess the robustness of the deterministic results obtained earlier. Given a random variable X, an inter-quantile width of z% is the pair of lower and upper bounds, x_L and x_U for which the cumulative probability distribution is $P(X<=x_L) = (100\text{-}z)/2$ % and $P(X<=x_U) = (100 - (100\text{-}z)/2)$ %. The mean and standard deviation of g_{1i}, g_{2i} and g_3 are calibrated using the observations from the year 2006 to 2015, smoothed over three-year periods. The corresponding data is described in Table A9 of SI.

4.3.5 Data collection and description

In this paper, the study period spans from 2001 to 2030. Energy and CO_2 emissions of each energy-intensive sub-sector from 2001 to 2015 at the provincial level are from Shan et al. (2018). The emissions include both energy- and process-related (cement) CO_2 emissions. Emissions from the generation of electricity and heat (irrespective of the consuming sector) are allocated to the electricity sector. The IVA data from 2001 to 2007 were collected from the China Statistical Yearbook (NBSC, 2002-2008). Since the IVA data for industrial sub-sectors were only published before 2007, the data of 2008-2015 were calculated using the officially reported annual average growth rates of IVA from the website of National Bureau of Statistics of China (NBSC, 2009-2016). The IVA is converted into 2000 constant price based on the industrial producer price index. The GDP from year 2001 to year 2016 was collected from the China Statistic Yearbook (NBSC, 2002-2017). The predicted growth rates of GDP from 2017 to 2030 were taken from the World Bank (World Bank, 2017) (Table A1 of SI). The growth rates of other indicators (output-based carbon intensity, share of IVA of each energy-intensive sub-sector, and share of IVA of energy-intensive industries in GDP) are from our calculation, which are listed in the SI (Tables A1-2).

The indicators in DDF model include three inputs: capital stock (billion yuan/yr), labor (10^4 people/yr) and energy consumption (Mtce (million tons coal equivalent)/yr); one desirable output, gross output (billion yuan/yr); and one undesirable output, CO_2 emissions ($MtCO_2$/yr). The capital stock[7] from 2001 to 2015 is calculated by the original value of fixed assets, accumulated depreciation and fixed asset investment, taken respectively from the China Industry Economy Yearbook (NBSC, 2001-2016) and the Statistical Yearbook of The Chinese Investment in Fixed Assets (NBSC, 2002-2016a). We consider 2000 as the base year and the capital stock in 2000 is obtained by the difference between original value of fixed assets and accumulated depreciation. When calculating the capital stock, the fixed asset investment has been converted into 2000 constant price using the double deflation method by fixed asset investment price index (NBSC, 2002-2016b). Labor and gross output value from year 2001 to year 2015 are also from the China Industry Economy Yearbook (NBSC, 2001-2016). The gross output has been converted into 2000 constant prices.

Table A10 of SI shows the descriptive statistics for the input and output indices of DDF method. Tables A11-16 show the correlation coefficients for the input and output indices. It can be seen that the correlation coefficients between the outputs and inputs are all significantly positive at the 5% level (P value < 0.05), indicating that the outputs will increase as the inputs increase. The P value, calculated by the Stata software, is used to evaluate whether the results of correlation coefficient are significant. Thus, the technical efficiency analysis is feasible. Note that the population of DMUs considered in this study are the 30 Chinese provinces and we have used all of them in the analysis. Therefore, the sample is the population and thus representative by definition.

Data for a few specific sectors and years at the provincial level was missing: the labor of the *electricity* sector in 2004 in 30 provinces and the labor of all sectors in 2012 and 2015 in some provinces (Hebei, Liaoning, Shanghai, Zhejiang, Fujian, Shandong, Henan, Hubei, Guangxi, Hainan, Guizhou, Yunnan, Shaanxi, Qinghai, Ningxia and Xinjiang), which means there is 30 missing points in 2004 for *electricity* sector and 16 missing points in 2012 and 2015 for all six sectors. These values inferred using the linear interpolation method (Tian and Lin, 2018) between the preceding and subsequent year. The number of missing points is 16-30, out of a total of 150 points (30 regions times 5 indicators) used in the DEA study, so we believe that the uncertainty introduced by the interpolation procedure is minor and it is not necessary to use a more complex interpolation procedure.

4.4. Results

We begin this section by presenting the patterns of historical CO_2 emissions and carbon intensity of energy-intensive industries and its component sectors. Then, we display the impact of regional convergence in energy-intensive industries on absolute CO_2 emissions. Afterwards, we present the contribution of regional convergence in energy-intensive industries to meeting China's emissions goals in 2020 and 2030. Finally, we analyze the uncertainty of the CO_2 emissions projections.

4.4.1. Patterns of historical CO_2 emissions

The CO_2 emissions of energy-intensive industries and its constituent sectors are shown in Fig. 2. The growth trend of national CO_2 emissions is similar to that of energy-intensive industries, which accounted for ~80% of total emissions from 2001 to 2015. CO_2 emissions of energy-intensive industries grew fast before 2011 (CO_2 emissions in 2011 were three times those of 2001), and

[7] The capital stock from 2001 to 2015 in this paper is calculated using the perpetual inventory method as K_t = K_{t-1}*(1-δ_t)+I_t/P_t. K_t, K_{t-1}, δ_t, I_t and P_t respectively represent the capital stock in year *t*, *t-1*, the depreciation rate in year t, fixed investment and the fixed asset investment price index in year *t*.

afterwards they became relatively flat. The *electricity* sector accounted for 46-52% of national total emissions, followed by the *ferrous metals* (10-15%) and *non-metallic products* (9-10%) sectors. The historical data also shows that there were significant differences in regional CO_2 emissions in each specific sector (shown in Fig. A1 of SI). For example, Shandong, Hebei, Shandong, Shanxi, Hubei and Henan had the most CO_2 emissions in *electricity*, *ferrous metals*, *non-metallic products*, *petroleum*, *chemicals* and *non-ferrous metals* sectors with an average value of 307.7 $MtCO_2$/yr, 203 $MtCO_2$/yr, 53.7 $MtCO_2$/yr, 37 $MtCO_2$/yr, 14.6 $MtCO_2$/yr and 10.7 $MtCO_2$/yr during the study period, respectively, while emissions from the smallest provinces were less than 1 $MtCO_2$/yr except for the *electricity* sector (12.5 $MtCO_2$/yr). This does not necessarily mean that provinces with large emissions are worse performers since there are significant differences in the overall size and composition of the industrial sector of different provinces. These patterns of historical CO_2 emissions show that there are heterogeneities in CO_2 emissions not only among industries but also across regions.

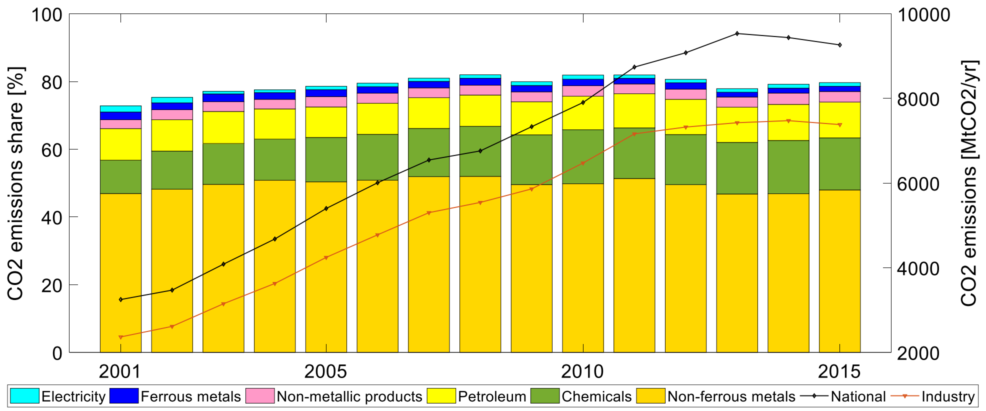

Fig. 2. Historical CO_2 emissions of energy-intensive industries from 2001 to 2015 (Industry = Energy-intensive industries). Bars indicate the contribution of energy-intensive sub-sectors to national total emissions (unit: %); the black line indicates national total emissions and the red line indicates total emissions of energy-intensive industries (unit: $MtCO_2$/yr).

The historical carbon intensities of each energy-intensive sub-sector are shown in Fig. 3. The figure shows not only the historical average national carbon intensity (historical average BAU carbon intensities) but also the median carbon intensity of sub-sectors in provinces at the production frontier (Frontier) as defined in section 4.3.2 and the lowest carbon intensity of sub-sectors as found in any of the different provinces (which in this study are regarded as BAT). There was a wide gap between BAU, Frontier and BAT carbon intensities, reflecting a wide difference in past carbon intensity performance between sub-sectors in different provinces. The gap between the BAU and Frontier carbon intensities was expanding in the *petroleum*, *chemicals* and *electricity* sectors, with values between Frontier to BAU decreasing from 70.3% in 2001 to 45.1% in 2015, 82.4% in 2001 to 30.7% in 2015, and 91.8% in 2001 to 54.2% in 2015, respectively. For and *ferrous metals* sector, the gap of carbon intensities between BAU and Frontier was relatively constant with only minor fluctuations. On the contrary, the carbon intensity between Frontier and BAU for the *non-metallic products* and *non-ferrous metals* sectors respectively increased from 69.4% of in 2001 to 76.5% in 2015 and 7.5% in 2001 to 23.1% in 2015, indicating that their technology gaps between BAU, i.e. the sector's Chinese average, and Frontier were narrowing. Regarding to the gaps of carbon intensity between BAU and BAT, there was an increasing trend in the sectors of *chemicals*, *non-ferrous metals* and *electricity*, while a narrowing trend appeared in the sectors of *petroleum* and *ferrous metals*. For *non-metallic products* sector, the carbon intensity under BAT relative to BAU was relatively constant (around 25%). Taken together these observations indicate that regional technological heterogeneities persisted in most sectors and therefore historical regional convergence has been minimal. This in turn means that there is a large potential for regional convergence, i.e., moving from the BAU towards Frontier and BAT past performance would lead to significant improvements in the carbon intensity of most industry sub-sectors.

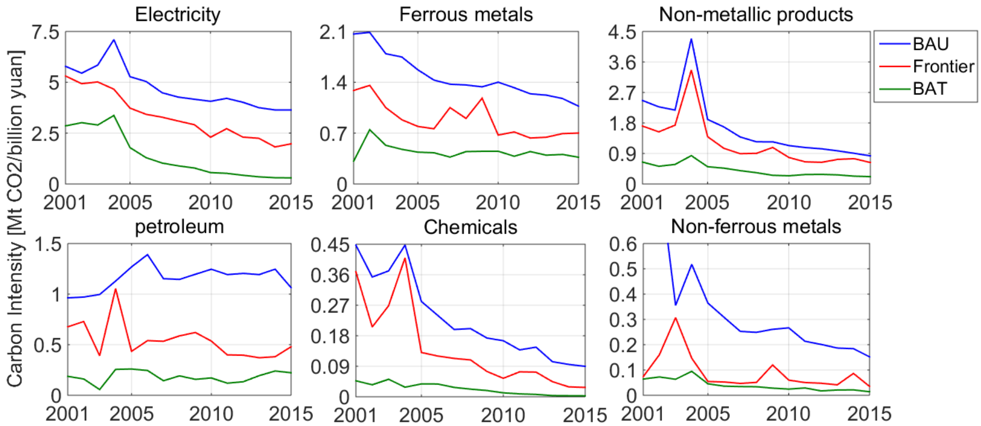

Fig. 3. Historical output-based carbon intensity of each energy-intensive sub-sector. BAU is the historical average carbon intensity of the sub-sector in China. BAT is the historical carbon intensity in the province where the sub-sector performed best. Frontier reflects the carbon intensity of the sub-sector in frontier provinces as defined in section 4.3.2. The BAU carbon intensity of the *non-ferrous metals* sector in 2001 and 2002 were, respectively, 0.98 and 0.87 Mt CO_2/billion yuan.

4.4.2. Assessment of regional convergence on CO_2 emissions

Table 1. Future CO_2 emissions of energy-intensive industries under different scenarios (Unit: $MtCO_2$/yr).

Scenarios/Year	2016	2018	2020	2022	2024	2025	2026	2028	2030
BAU	7482.7	7676.3	7829.0	7922.6	8022.8	8075.2	8083.3	8103.0	8127.6
Frontier	4337.0	4429.2	4497.6	4532.4	4571.6	4593.0	4589.5	4580.4	4533.0
BAT	1200.2	1224.0	1240.1	1245.9	1251.9	1254.9	1250.8	1242.7	1234.7

Note: BAU means business as usual and BAT is the best available technology scenario.

In this subsection we present forecasts of future CO_2 emissions of energy-intensive industries under the three scenarios, and examine how regional convergence might impact CO_2 emissions. Table 1 shows the future CO_2 emissions of energy-intensive industries as a whole and Fig. 4 presents the CO_2 emissions of its specific sectors. Under the BAU scenario, the CO_2 emissions of energy-intensive industries display an upward trend, rising from 7382.8 $MtCO_2$/yr in 2015 to 8127.6 $MtCO_2$/yr in 2030. The CO_2 emissions of the *petroleum*, *chemicals* and *ferrous metals* sectors decrease from 2015 to 2030 while the emissions from the other three sectors increase. The total CO_2 emissions of energy-intensive industries as a whole under the alternative scenarios are much lower than those under BAU. Under the frontier scenario, energy-intensive industries could peak its CO_2 emissions in 2025 at a value of 4593.0 $MtCO_2$/yr. The CO_2 emissions of the *petroleum* and *chemicals* sectors decrease slightly from 2015 to 2030. On the contrary, the CO_2 emissions from the *non-metallic products* and *non-ferrous metals* sectors increase from 2015 to 2030. For the *electricity* and *ferrous metals* sectors, CO_2 emissions will peak around 2018 and 2025, respectively. Under the BAT scenario, despite much lower CO_2 emissions compared with the BAU and frontier scenarios, the peak of CO_2 emissions of the *petroleum*, *chemicals* and *ferrous metals* sectors is reached around 2025, while it is reached a little earlier by the *electricity* sector (2020). Meanwhile, CO_2 emissions of *non-ferrous metals* decrease from 2015 to 2030. Only the sector of *non-metallic products* has higher CO_2 emissions year by year. In summary, we find that under BAU the CO_2 emissions of energy-intensive industries as a whole and the *electricity* sector in particular are growing continuously from 2015 to 2030, while they will peak before 2030 under alternative scenarios.

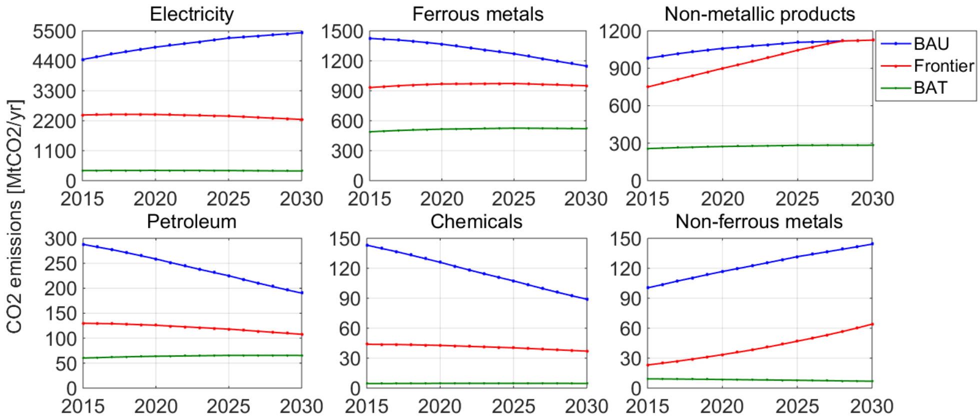

Fig. 4. CO_2 emissions of the six energy-intensive sub-sectors under the three scenarios. BAU means business as usual scenario and BAT is the best available technology scenario. CO_2 emissions of *non-metallic products* sector in the frontier scenario are higher than those in BAU in the years 2028-2030, indicating that technology convergence occurs between BAU and frontier scenario. Therefore, we assume that the CO_2 emissions in frontier scenario are equal to those in BAU.

The impact of regional convergence on CO_2 emissions is reflected in the differences between CO_2 emissions in BAU and alternative scenarios. If the frontier scenario can be reached, total annual emissions will be reduced by 42.0-44.2% from 2016 to 2030 compared to BAU, of which the *electricity* sector contributes to 28.4-39.2%. The reduction potential is even more substantial under the BAT scenario. The total annual emission reduction increase from 6282.5 $MtCO_2$/yr in 2016 to 6892.9 $MtCO_2$/yr in 2030, accounting for 84.0% of BAU emissions in 2016 and 84.8% in 2030. This emission reduction can be attributed mainly to the *electricity* sector (4173.2-5076.6 $MtCO_2$/yr), followed by the sectors of *non-metallic products* (737.9-842.3 $MtCO_2$/yr) and *ferrous metals* (627.6-920.1 $MtCO_2$/yr). The remaining three sectors account for no more than 5% of the emissions reduction potential from 2016 to 2030. In both frontier and BAT scenarios, the reduction potential of the *petroleum*, *chemicals* and *ferrous metals* sectors will be smaller in 2030, indicating that the gaps of CO_2 emissions between BAU and alternative scenarios are narrowing for these three sectors.

However, the gap of CO_2 emissions between BAU and the frontier scenario in the sector of *non-metallic products* is narrowing while it is widening under the BAT scenario. The reduction potential of the *non-ferrous metals* sector under the frontier scenario increases from 2016 to 2025, and then decreases until 2030, while it increases from 2016 to 2030 under the BAT scenario. The emission reduction potential of the *electricity* sector increases over time under both the frontier and BAT scenarios.

4.4.3. Contribution to emissions goals

It should be remembered that China promised to achieve a 40-45% reduction in carbon intensity in 2020 and 60-65% reduction in 2030 compared to 2005. Fig. 5 shows the carbon intensity reduction of energy-intensive industries as a whole and each specific sector thereof in time series compared to the 2005 levels. Even under BAU, energy-intensive industries have a positive contribution to China's emissions goals, with carbon intensity of every sector decreasing by more than the nationally-mandated averages. It can be seen that carbon intensity of energy-intensive industries in 2014 was 43.3% lower than that in 2005, indicating that the 2020 emissions goals have already been achieved (in energy-intensive industries). The 2020 emission reduction goal are realized by the *chemicals* sector in 2010, by *non-metallic products* in 2010 and *non-ferrous metals in* 2011. Note however, that indirect CO_2 emissions from electricity and heat are allocated to the *electricity* sector, if such emissions were taken into account (a consumption-based approach) this progress would have been slower. The carbon intensity of the *ferrous metals* sector is 59.2% of 2005 in 2017, indicating that the 2020 emissions goal can be achieved before 2020. However, the *petroleum* sector will reach the 2020 goal in 2021. Additionally, the 2030 emission goal can be reached by the energy-intensive industries on average in 2020 and five of six sub-sectors before 2030. On the contrary, the carbon intensity reduction of *electricity* sector remains constant (around 30%), indicating that the 2020 and 2030 emissions goals cannot be achieved by the *electricity* sector under BAU. Note that so far in this analysis we have considered that the 2020 and 2030 emissions goals refer to 40% and 60% carbon intensity reduction relative to 2005. If the values selected are 45% and 65%, the years in which goals are achieved will be postponed by one or two years.

Fig. 5 also shows the carbon intensity reduction of energy-intensive industries as well as its constituent sectors from 2005 to 2030 under alternative scenarios. The data from 2005 to 2015 is BAU data and the carbon intensity reduction from 2016 to 2030 under the frontier and BAT scenarios is calculated by comparison with the BAU carbon intensity in 2005. It can be seen that there is a discontinuous jump in carbon intensity reduction in 2016 under the frontier and BAT scenarios, as an unrealistic instantaneous adoption of new technology in many provinces is implied. Of course, a realistic policy of regional convergence would involve an adaptation period during which the new technology diffuses across regions. Estimating the speed of such diffusion over time would imply using additional, uncertain assumptions. Fig. 5 hence has to be interpreted as simply showing the theoretical emission reduction potential if frontier or BAT technologies would be implemented in 2016 in all of China. The actual emission reductions that can be realized by a regional convergence process on the short term are obviously (much) lower.

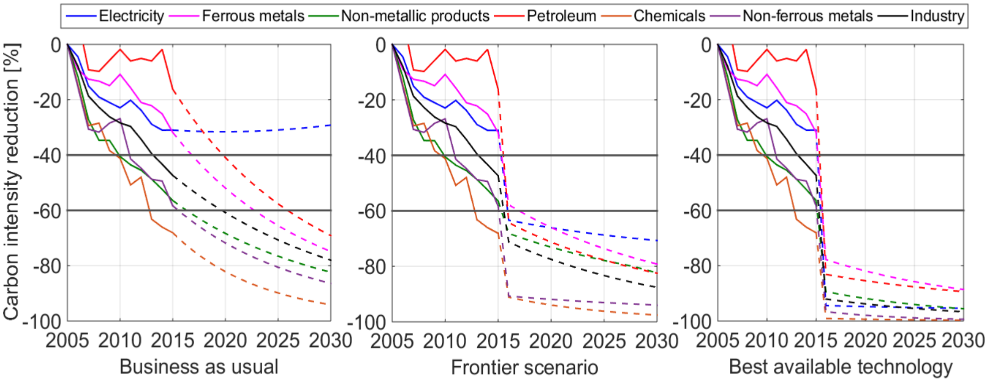

Fig. 5. The contribution of energy-intensive industries to China's emissions goals, measured by carbon intensity reduction (%) relative to BAU-2005, under different regional convergence scenarios. The solid lines are historical data and the dashed lines are forecast data. Note again that the historical data are real data but reflect a different selection of Chinese provinces for which an average carbon intensity is calculated (BAU: Chinese average; BAT: region with lowest carbon intensity of that sub-sector; Frontier: provinces at the frontier as defined in section 4.3.2). The horizontal solid gray lines (-40% and -60%) are the 2020 and 2030 emissions goals. "Industry" is energy-intensive industries as a whole. Values larger than zero are omitted from the figure.

Under the BAU scenario energy-intensive industries as a whole and every constituent sector thereof except *electricity* meet both carbon intensity goals, with the *electricity* sector's improvement never reaching beyond a 40% reduction in the whole study period. In contrast to the BAU scenario, under the frontier and BAT scenarios the *electricity* sector performs better, achieving both 2020 and 2030 emissions goals. For the energy-intensive industries as a whole, the carbon intensity could in theory be reduced by 71.2% and 92.0% in 2016, respectively under the frontier and BAT scenarios, relative to BAU, and would keep decreasing further thereafter. The frontier and BAT scenarios show a large reduction potential for the carbon intensity of each sector, relative to BAU, ranging from 57.8 % to 91.1% in 2016 under the frontier scenario for the sectors of *ferrous metals* and *chemicals*, respectively, and ranging from 77.8% to 99.1% in 2016 under the BAT scenario also for the sectors of *ferrous metals* and *chemicals*, respectively. This shows that regional convergence in the energy-intensive industries offers a large potential for carbon intensity reduction. This may be helpful for China to achieve the emissions goals, if it is necessary to offset increases in emissions stemming from other economic activities.

4.4.4. Uncertainty analysis

Due to the uncertainties surrounding forecast data in this paper, we conducted an uncertainty analysis to inform the robustness of the results using the method of Monte Carlo simulation. As described in Section 3.4 we constructed an alternative stochastic method, from which the inter-quantile width (IQW) of the prediction could be obtained. Fig. 6 shows the predicted inter-quantile widths of CO_2 emissions up to 2030 for the six sectors within the energy-intensive industries under the business-as-usual scenario. The projections made earlier in this paper using a deterministic model are all within the 90% and 50% inter-quantile widths of the stochastic model. We now describe in detail the 90%-IQW ranges in 2030. The *non-ferrous metals* sector has the widest relative 90%-IQW, which ranging from 131.9 $MtCO_2$/yr to 157.6 $MtCO_2$/yr represents 17.8% of the deterministic value of 144.2

$MtCO_2$/yr, while the sector with the narrowest relative 90%-IQW is *non-metallic products*, with the range (1070.7-1183.0 $MtCO_2$/yr) representing 9.8% of the predicted emissions (1148.1 $MtCO_2$/yr). The relative 90%-IQW of the other sectors lies within these two extremes: the 90%-IQW of the *petroleum* sector (172.3-201.7 $MtCO_2$/yr) is 15.4% of the forecast value (190.3 $MtCO_2$/yr); the 90%-IQW of the *electricity* sector (5053.5-5828.4 $MtCO_2$/yr) is 14.3% of 5430.1 $MtCO_2$/yr; the 90%-IQW of the *chemicals* sector (81.8-94.0 $MtCO_2$/yr) is 13.7% of 89.0 $MtCO_2$/yr; and the 90%-IQW of the *ferrous metals* sector (1078.8-1222 $MtCO_2$/yr) is 12.5% of 1148.1 $MtCO_2$/yr. For every sector considered the 90% inter-quantile width is a range of 10-18% of the forecast values. The fact that relative inter-quantile widths are all within a narrow range means that it is sectors whose forecast emissions are higher that most contribute to the error budget.

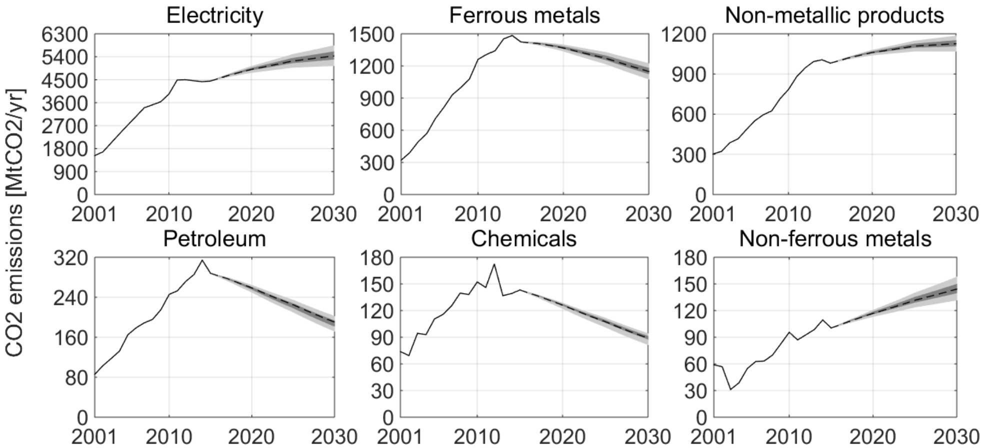

Fig. 6. Uncertainty of the CO_2 emissions forecast under the BAU scenario. The black solid line is historical data, the black dashed line is the deterministic prediction, the dark shaded region is the 50% inter-quantile width and the light shaded region is the 90% inter-quantile width.

4.5. Discussion

Given that technological improvements are now playing a vital role in climate change (Zhao et al., 2015), we explored the impact of regional convergence on the CO_2 emissions of energy-intensive industries, where the regional convergence can be achieved by technological diffusion and adoption, finding that regional convergence can reduce CO_2 emissions significantly. From the patterns of historical data, Fig. 3 shows that the *non-metallic products* sector exhibits a trend of regional convergence between BAU and frontier, with the ratio of the carbon intensity of the frontier and BAU scenarios increasing from 69.4% in 2001 to 76.5% in 2015. Therefore, with the impact of regional convergence, the CO_2 emissions in frontier scenario are higher than those in BAU from 2028 to 2030. The frontier scenario means all regions tend to be technically efficient and it is a better scenario for emissions reduction than BAU, so we assume that the CO_2 emissions of *non-metallic* sector from 2028 to 2030 are equal to those in BAU (shown in Fig. 4). Moreover, the *chemicals* and *electricity* sectors exhibit a growing technology gap. Such a phenomenon can be explained by the economic theory of ‘backward disadvantage’, according to which the more a province lags from the frontier, the harder it will be to catch up with it (Yan et al., 2017). ‘Backward disadvantage’ is mainly caused by the insufficient investment to technological innovation, lack of human capital or low level of financial development (Aghion and Howitt, 2006). However, there is a competing well-known hypothesis, the 'advantage of backwardness' (Yan et al., 2017). According to this hypothesis, the further a regional economy falls behind the national technological leaders, the easier it is for that economy to move towards the technological frontier simply by technological diffusion and adoption. Therefore, provinces whose technology level is far below the frontier/best available technology can decrease their carbon intensities by joint research with and technology transfer from more advanced provinces. To counteract 'backward disadvantage' the government could provide financial subsidies as an incentive for the laggards to adopt technologies introduced from more advanced provinces.

In addition, this paper explores the contribution of regional convergence in energy-intensive industries to China's emissions goals. Despite the significant impact of regional convergence on CO_2 emissions for most sectors, its contribution to China's emissions goals varies across sectors. Considering the contribution of energy-intensive industries to China's emissions goals, many previous studies pointed out that China (China's industrial sector) can achieve the emissions goals with the current policies (Cansino et al., 2015; Wang et al., 2016; Xu et al., 2017; Zhang et al., 2017). On the contrary, some studies showed that existing policies are not enough for China and energy structure optimization and energy efficiency improvement are needed (Yuan et al., 2012; Elzen et al., 2016). Our paper shows that even under business as usual energy-intensive industries can achieve the emissions goals. Regional convergence offers a large scope for the reduction of emissions in energy-intensive industries, and thus can help achieving the emissions goals. The sectors of *non-metallic products* and *electricity*, especially the latter, exhibit the largest potential for such a decrease. In the hypothetical scenario that the frontier and BAT technologies could be implemented in 2016 in all over China, the CO_2 emissions of the *electricity* sector would peak in 2018 (2020) and the peak for energy-intensive industries would be around 2025.

Even though regional convergence can, in principle, significantly reduce CO_2 emissions from energy-intensive industries if a realistic time period is allowed for diffusion of frontier and BAT technologies, it is worth considering potential barriers to regional convergence. (1) The outputs of each industry are not necessarily homogeneous across regions and so it might happen that one region specializes in high-value products and another in low-value products. If the emissions per unit of mass are identical, the emissions per unit of monetary output will differ. In this case, the difference in performance across regions is not of a technical nature, and hence cannot be solved by technological transfer, but is of a business nature, and can only be solved by improved product design, marketing and similar operations. (2) Regional convergence might be particularly difficult for power generation, as the technologies (thermal, hydro, nuclear, wind and solar) vary significantly in different provinces (shown in Tables A18-20 of SI). The energy mix of a particular province is in part explained by the resource endowments of that province and thus regional convergence might be difficult. Note that thermal power is still the primary source for power generation in China (NBSC, 2006-2016; CEC, 2016) as well as most of provinces except for Sichuan, Yunnan, Qinghai, Hubei and Guangxi. In general, when conducting technology transfer or joint research of technology in the *electricity* sector, provinces should take their own resource characteristics and advantages into consideration.

4.6. Conclusions

Given that energy-intensive industries account for about 80% of the CO_2 emissions of China, they are a key component in China's ability to achieve its emissions goals. Motivated by the idea that each particular sector within energy-intensive industries has similar technical characteristics that can be replicated across regions, this study explores the impact of regional convergence in the CO_2 emissions of energy-intensive industries until 2030. To address this issue, three scenarios are established which can be used to reflect the degree of regional convergence of a given sector across all provinces. The findings show that the potential impact of this regional convergence on CO_2 emissions is significant. If the frontier scenario can be reached, the CO_2 emissions of energy-intensive industries can be reduced by 42.0-44.2%; and the reduction reaches more than 80% if the best-available technology scenario is reached. The emission reduction potential is highest in the *electricity* and *ferrous metals* sectors. Even under business as usual, the carbon intensity of energy-intensive industries can achieve the emissions goals before the targeted years, with the goals being realized much earlier under regional convergence. The contributions of regional convergence in the *chemicals* and *electricity* sectors are the most significant to China’s emissions goals, especially in *electricity* sector. Under business as usual there is a steady increase in the total volume of emissions from energy-intensive industries in the period under study, but if there is regional convergence these emissions will peak in 2025 (both frontier and best available technology) and decrease thereafter.

The historical patterns of carbon intensity do not show an obvious trend of convergence, except in the sector of *non-metallic products*. In order to promote regional convergence, the Chinese government should provide policy instruments for the introduction and diffusion of technologies across provinces. Meanwhile, local governments, especially those who employ inefficient technologies, need to actively conduct joint research and introduce advanced technologies under the guidance of national policies. Of course, the adoption of new technologies should take into account local characteristics and promote innovation, in order to achieve a better adaptation. As a supplementary policy, fiscal policy could be used in conjunction with regulation and guiding policies. For example, the cost of technology introduction could be reduced through fiscal means, as cost is a major factor holding back technology convergence (Hao and Peng, 2017). The Chinese government could reduce the purchase tax or provide financial subsidies for the adoption of efficient technology. In particular, a significant impact of regional convergence on CO_2 emissions and emissions goals manifests in the *electricity* sector, so this sector should be prioritized when encouraging technology convergence.

References

Aghion P, Howitt P, 2006. Joseph Schumpeter lecture appropriate growth policy: a unifying framework. Journal of the European Economic Association 4(2-3): 269-314.

Alexiadis S, 2011. Does technological heterogeneity promote regional convergence? Implications for regional policy and entrepreneurship. Annals of Innovation & Entrepreneurship 2(1): 6001-6008.

Bataille C, Åhman M, Neuhoff K, Nilsson LJ, Fischedick M, Lechtenbohmer S, et al., 2018. A review of technology and policy deep decarbonization pathway options for making energy-intensive industry production consistent with the Paris agreement. Journal of Cleaner Production 187: 960-973.

Cansino JM, Román R, Rueda-Cantuche JM, 2015. Will China comply with its 2020 carbon intensity commitment? Environmental Science & Policy 47:108-117.

China Electricity Council (CEC), 2016. Annual development report of China's power sector 2015. Beijing (In Chinese).

Ciscar JC, Soria A, 2000. Economic convergence and climate policy. Energy Policy 28(11): 749-761.

Costantini V, Crespi F, Martini C, Pennacchio L, 2015. Demand-pull and technology-push public support for eco-innovation: The case of the biofuels sector. Research Policy 44(3): 577-595.

Costantini V, Crespi F, Palma A, 2017. Characterizing the policy mix and its impact on eco-innovation: A patent analysis of energy-efficient technologies. Research Policy 46(4): 799-819.

Cui LB, Fan Y, Zhu L, Bi QH, 2014. How will the emissions trading scheme save cost for achieving China's 2020 carbon intensity reduction target? Applied Energy 136: 1043-1052.

Elzen MD, Fekete H, Höhne N, Admiraal A, Forsell N, Hof AF, Olivier JGJ, Roelfsema M, van Soest H., 2016. Greenhouse gas emissions from current and enhanced policies of China until 2030: Can emissions peak before 2030? Energy Policy 89: 224-236.

Fais B, Sabio N, Strachan N., 2016. The critical role of the industrial sector in reaching long-term emission reduction, energy efficiency and renewable targets. Applied Energy 162: 699-712.

Fan Y, Liu LC, Wu G, Tsai HT, Wei YM, 2007. Changes in carbon intensity in China: empirical findings from 1980-2003. Ecological Economics 62(3-4): 683-691.

Färe R., Grosskopf S., Pasurka C, 2007. Environmental production functions and environmental directional distance functions. Energy 32: 1055-1066.

Friedlingstein P, Andrew RM, Rogelj J, Peters GP., Canadell JG., Knutti R., et al., 2014. Persistent growth of CO_2 emissions and implications for reaching climate targets. Nature Geoscience 7(10): 709-715.

Gries T, Grundmann R, Palnau I, Redlin M, 2018. Technology diffusion, international integration and participation in developing economies - a review of major concepts and findings. International Economics & Economic Policy 15(1): 215-253.

Guan D, Klasen S, Hubacek K, Feng KS., Liu Z., He KB., Geng Y., Zhang Q., 2014. Determinants of stagnating carbon intensity in China. Nature Climate Change 4(11): 1017-1023.

Han L, Han B, Shi XP., Su B., Lv X., Lei X., 2018. Energy efficiency convergence across countries in the context of China's Belt and Road initiative. Applied Energy 213: 112-122.

Hao H, Geng Y, Li W, Guo B., 2015. Energy consumption and GHG emissions from China's freight transport sector: Scenarios through 2050. Energy Policy 85: 94-101.

Hao Y, Peng H., 2017. On the Convergence in China's Provincial Per Capita Energy Consumption: New Evidence from a Spatial Econometric Analysis. Energy Economics 68: 31-43.

International Energy Agency (IEA), 2017. World Energy Outlook 2017. IEA, Paris, France <www.iea.org>.

Kounetas KE., 2018. Energy consumption and CO_2, emissions convergence in European Union member countries. A tonneau des Danaides? Energy Economics 69: 111-127.

Li F, Xu Z, Ma H., 2018. Can China achieve its CO_2 emissions peak by 2030? Ecological Indicators 84: 337-344.

Li HQ, Wang LM, Shen L, Chen FN, 2012. Study of the potential of low carbon energy development and its contribution to realize the reduction target of carbon intensity in China. Energy Policy 41: 393-401.

Li K, Lin B., 2016. China's strategy for carbon intensity mitigation pledge for 2020: evidence from a threshold cointegration model combined with Monte-Carlo simulation methods. Journal of Cleaner Production 118: 37-47.

Liu L, Zong H, Zhao E, Chen C, Wang J., 2014. Can China realize its carbon emission reduction goal in 2020: From the perspective of thermal power development. Applied Energy 124: 199-212.

Liu X, Mao G, Ren J, Li RYM, Guo J, Zhang L., 2015. How might China achieve its 2020 emissions target? A scenario analysis of energy consumption and CO_2 emissions using the system dynamics model. Journal of Cleaner Production 103: 401-410.

Mi Z, Wei Y M, Wang B, Meng J., Liu Z., Shan YL., Liu JR., Guan DB., 2017. Socioeconomic impact assessment of China's CO_2, emissions peak prior to 2030. Journal of Cleaner Production 142(4): 2227-2236.

Mishra V, Smyth R., 2017. Conditional Convergence in Australia's Energy Consumption at the Sector Level. Energy Economics 62: 396-403.

National Bureau of Statistics of China (NBSC) (2001-2016). China Industry Economy Yearbook. China Statistical Press, Beijing (In Chinese).

National Bureau of Statistics of China (NBSC) (2002-2016a). Statistical Yearbook of The Chinese Investment In Fixed Assets. China Statistical Press, Beijing (In Chinese).

National Bureau of Statistics of China (NBSC) (2002-2008). China Statistics Yearbook. China Statistical Press, Beijing (In Chinese).

National Bureau of Statistics of China (NBSC) (2002-2016b). China Statistics Yearbook. China Statistical Press, Beijing (In Chinese).

National Bureau of Statistics of China (NBSC) (2002-2017). China Statistics Yearbook. China Statistical Press, Beijing (In Chinese).

National Bureau of Statistics of China (NBSC) (2016). China Statistics Yearbook. China Statistical Press, Beijing (In Chinese).

National Bureau of Statistics of China (NBSC) (2006-2016). China Energy Statistical Yearbook. China Statistical Press, Beijing (In Chinese).

National Bureau of Statistics of China (NBSC) (2009-2016). Growth rate of industrial value added by sector 2009-2016. URL: < http://data.stats.gov.cn/easyquery.htm?cn=A01>.

Niu SW., Liu YY., Ding YX., Qu W., 2016. China’s energy systems transformation and emissions peak. Renewable & Sustainable Energy Reviews 58: 782-795.

Raftery AE, Zimmer A, Frierson DMW, Startz R., Liu PR., 2017. Less than 2 °C warming by 2100 unlikely. Nature Climate Change 7(9): 637-641.

Sachs JD, Warner AM, 1995. Economic Convergence and Economic Policies. Case Network Studies & Analyses 65(4): 900-913.

Shan YL., Guan DB., Zheng HR., Ou JM., Li Y., Meng J., Mi ZF., Liu Z., Zhang Q., 2018. Data descriptor: China CO_2 emission accounts 1997-2015. Scientific Data. Shan, Y. et al. Figshare https://doi.org/10.6084/m9.figshare.c.3936484.v1 (2017).

Shao S, Huang T, Yang LL, 2014. Using latent variable approach to estimate China’s economy-wide energy rebound effect over 1954-2010. Energy Policy 72: 235-248.

Su B, Ang BW, 2017. Multiplicative structural decomposition analysis of aggregate embodied energy and emission intensities. Energy Economics 65: 137-147.

Tian P, Lin BQ, 2018. Regional technology gap in energy utilization in China's light industry sector: Non-parametric meta-frontier and sequential DEA methods. Journal of Cleaner Production 178: 880-889.

Wang J, Hu MM, Rodrigues JFD, 2018a. An empirical spatiotemporal decomposition analysis of carbon intensity in China’s industrial sector. Journal of Cleaner Production 195: 133-144.

Wang J, Hu MM, Rodrigues JFD, 2018b. The evolution and driving forces of industrial aggregate energy intensity in China: An extended decomposition analysis. Applied Energy 228: 2195-2206.

Wang J, Zhang KZ, 2014. Convergence of carbon dioxide emissions in different sectors in China. Energy 65: 605-611.

Wang J, Zhao T, Wang Y., 2016. How to achieve the 2020 and 2030 emissions targets of China: Evidence from high, mid and low energy-consumption industrial sub-sectors. Atmospheric Environment 145: 280-292.

Wang J, Zhao T, Zhang XH, 2017. Changes in carbon intensity of China's energy-intensive industries: a combined decomposition and attribution analysis. Natural Hazards 88(3): 1655-1675.

Wang K, Wang C, Lu XD, Chen JN, 2007. Scenario analysis on CO_2 emissions reduction potential in China's iron and steel industry. Energy Policy 35(4): 2320-2335.

Ward H, Radebach A, Vierhaus I, Fügenschuh A, Steckel JC, 2017. Reducing global CO_2 emissions with the technologies we have. Resource and Energy Economics S0928765516302123.

World Bank, 2017. Global Economic Prospects. <http://www.worldbank.org/en/publication/global-economic-prospects >.

Wu J, Wu Y, Guo X, Cheong TS., 2016. Convergence of carbon dioxide emissions in Chinese cities: A continuous dynamic distribution approach. Energy Policy 91: 207-219.

Wu QL, Peng CY, 2016. Scenario analysis of carbon emissions of China's electric power industry up to 2030. Energies 9(12): 988-1005.

Xiao H, Wei Q, Wang H., 2014. Marginal abatement cost and carbon reduction potential outlook of key energy efficiency technologies in China′s building sector to 2030. Energy Policy 69: 92-105.

Xie X, Shao S, Lin BQ, 2016. Exploring the driving forces and mitigation pathways of CO_2 emissions in China's petroleum refining and coking industry: 1995-2031. Applied Energy 184: 1004-1015.

Xu L, Chen N, Chen Z., 2017. Will China make a difference in its carbon intensity reduction targets by 2020 and 2030? Applied Energy 203: 874-882.

Yan Z, Du K, Yang Z, et al., 2017. Convergence or divergence? Understanding the global development trend of low-carbon technologies. Energy Policy 109: 499-509.

Yang H., Pollitt M., 2010. The necessity of distinguishing weak and strong disposability among undesirable outputs in DEA: environmental performance of Chinese fired power plants. Energy Policy 38(8): 4440-4444.

Yang S, Cao D, Lo K., 2018. Analyzing and optimizing the impact of economic restructuring on Shanghai's carbon emissions using STIRPAT and NSGA-II. Sustainable Cities & Society 40: 44-53.

Yi WJ, Zou LL, Guo J, Wang K, Wei YM, 2011. How can China reach its CO_2 intensity reduction targets by 2020? A regional allocation based on equity and development. Energy Policy 39(5): 2407-2415.

Yu SW, Zheng SH, Li X, Li LX, 2018. China Can Peak Its Energy-related Carbon Emissions before 2025: Evidence from Industry Restructuring. Energy Economics 73: 91-107.

Yuan J, Hou Y, Xu M., 2012. China's 2020 carbon intensity target: Consistency, implementations, and policy implications. Renewable and Sustainable Energy Reviews 16: 4970-4981.

Zhang J, Jiang H, Liu G, Zeng WH., 2018. A study on the contribution of industrial restructuring to reduction of carbon emissions in China during the five Five-Year Plan periods. Journal of Cleaner Production 176: 629-635.

Zhang N, Choi Y, 2014. A note on the evolution of directional distance function and its development in energy and environmental studies 1997–2013. Renewable and Sustainable Energy Reviews 33: 50-59.

Zhang X, Zhao X, Jiang Z, Shao S, 2017. How to achieve the 2030 CO_2 emission-reduction targets for China's industrial sector: Retrospective decomposition and prospective trajectories. Global Environ. Chang. 44: 83-97.

Zhang YG, 2010. Economic Development Pattern Change Impact on China's Carbon Intensity. Economic Research Journal 4: 120-133.

Zhao X, Burnett JW, Lacombe DJ, 2015. Province-level convergence of China's carbon dioxide emissions. Applied Energy 150: 286-295.

Zheng B, Zhang Q, Borken-Kleefeld J, Huo H, Guan D, Klimont Z, Peters GP, He K., 2015. How will greenhouse gas emissions from motor vehicles be constrained in China around 2030? Applied Energy 156: 230-240.

Zheng H, Shan Y, Mi Z, Meng J., Ou JM., Schroeder HK., Guan DB., 2018. How modifications of China's energy data affect carbon mitigation targets. Energy Policy 116: 337-343.

Zhou DQ, Wang Q, Su B, Zhou P., Yao LX., 2016a. Industrial energy conservation and emission reduction performance in China: A city-level nonparametric analysis. Applied Energy 166: 201-209.

Zhou P, Ang BW, Poh KL, 2008. A survey of data envelopment analysis in energy and environmental studies. European Journal of Operational Research 189: 1-18.

Zhou S, Wang Y, Yuan Z, OuXM., 2018. Peak energy consumption and CO_2, emissions in China's industrial sector. Energy Strategy Reviews 20: 113-123.

Zhou W, Wang T, Yu Y, Chen D, Zhu B., 2016b. Scenario analysis of CO_2 emissions from China's civil aviation industry through 2030. Applied Energy 175: 100-108.

Zhu BZ, Jiang MX, Wang KF, Chevallier JL, Wang P, Wei YM, 2018. On the road to China's 2020 carbon intensity target from the perspective of "double control". Energy Policy 119: 377-387.

Zhu BZ., Wang KF., Chevallier JL., Wang P., Wei YM., 2015. Can China achieve its carbon intensity target by 2020 while sustaining economic growth?. Ecological Economics 119: 209-216.

Zhu ZS, Liao H, Cao H S, Wang L., Wei YM., Yan JY., 2014. The differences of carbon intensity reduction rate across 89 countries in recent three decades. Applied Energy 113(6): 808-815.

Supplementary information

The supplementary information (SI) provides additional information for supporting the main text: (1) the growth rates of parameters in section 4.3.1; (2) the results of DDF; (3) the statistical description of data set used in DDF and the correlation coefficient test for the input and output data in DDF; (4) the smooth data of output-based carbon intensity used in the uncertainty analysis; (5) the predictions of national emissions and GDP; (6) the differences of CO_2 emissions across different regions for each energy-intensive sub-sector; and (7) the proportions of electricity generated by various technologies.

1. The growth rates of different parameters

This section is related to the predictions of CO_2 emissions in section 4.3.1 of the main text. The growth rates of industry share are from our own calculation (see section 4.3.1). The growth rates of GDP refer to World Bank (World Bank, 2017). The growth rates of national CO_2 emissions are from the prediction of IEA, World Energy Outlook 2017 (IEA, 2017).

Table A1. The assumed annual growth rates of industry share, national GDP and national emissions in the period 2016-2030 (Unit: %/year).

Growth rate								
Industry share (Gross output)	Industry share (Industrial value added)	National GDP						National CO_2 emissions
Fixed	Fixed	2017	2018	2019	2020	2021-2025	2026-2030	Fixed
1.36	0.80	6.8	6.4	6.3	6.2	5.8	5.2	1

Table A2. The assumed annual growth rates of sub-industry share and carbon intensity of six energy-intensive industries in the period 2016-2030 (Unit: %/year). The data set results from authors' own calculation, as explained in Section 4.3.1.

Sub-sector	Growth rate				
	Sub-sector share (Gross output)	Sub-sector share (Industrial value added)	Output-based carbon intensity		
	Fixed	Fixed	Business as usual	Fontier	Best technology
Petroleum sector	-3.73	-1.85	-3.37	-1.89	-0.12
Chemical sector	0.58	2.37	-11.92	-10.11	-8.87
Non-metallic products sector	1.25	1.19	-10.02	-8.11	-10.24
Ferrous metals sector	-1.08	-0.55	-2.94	-1.41	-1.14
Non-ferrous metals sector	3.07	4.20	-6.04	-1.85	-10.06
Electricity sector	0.30	-4.50	-7.26	-8.91	-8.72

2. The results of DDF

This section is related to section 4.3.2 of the main text. In Tables A3-8, values equal to 1 means the province is on the technical frontier.

Table A3. Regional DDF results of *petroleum* sector.

Symbol	Province	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
BJ	Beijing	0.78	0.87	0.77	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
TJ	Tianjin	1.00	0.99	1.00	0.94	1.00	0.94	0.87	0.68	0.44	0.59	0.69	0.65	0.84	0.62	1.00
HeB	Hebei	0.47	0.53	0.62	0.62	0.47	0.50	0.44	0.52	0.91	0.78	0.81	1.00	0.80	0.78	1.00
SX	Shanxi	0.03	0.05	0.11	0.15	0.08	0.12	0.08	0.08	0.07	0.07	0.05	0.04	0.04	0.05	0.05
IM	Inner Mongolia	0.47	1.00	0.10	0.07	0.07	0.11	0.08	0.10	0.03	0.12	0.09	0.08	0.21	0.30	0.15
LN	Liaoning	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.90	0.83	0.83	0.85	0.82	0.70
JL	Jilin	0.98	0.67	0.79	0.30	0.26	0.35	0.55	0.83	1.00	1.00	1.00	1.00	1.00	0.38	1.00
HLJ	Heilongjiang	0.58	0.51	0.56	0.35	0.30	0.33	0.18	0.15	0.10	0.09	0.07	0.06	0.07	0.08	0.08
SH	Shanghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.95	1.00	1.00	1.00
JS	Jiangsu	1.00	0.91	1.00	0.83	0.85	1.00	1.00	0.94	0.93	0.85	0.82	0.81	0.91	1.00	1.00
ZJ	Zhejiang	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AH	Anhui	0.60	0.65	0.71	0.87	1.00	0.86	0.71	0.67	0.27	0.82	0.57	0.62	0.72	0.81	0.75
FJ	Fujian	1.00	1.00	1.00	1.00	0.92	1.00	1.00	1.00	0.36	0.70	0.57	0.69	0.47	1.00	1.00
JX	Jiangxi	0.45	0.43	0.42	0.35	0.38	0.44	0.32	0.26	0.04	0.44	0.40	0.39	0.18	0.22	0.21
SD	Shandong	1.00	1.00	1.00	1.00	1.00	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
HeN	Henan	0.47	0.48	0.54	0.34	0.25	0.28	0.22	0.23	0.19	0.08	0.14	0.35	0.19	0.15	0.17
HuB	Hubei	1.00	1.00	0.96	0.95	0.87	1.00	0.85	0.78	0.60	0.53	0.46	0.39	0.65	0.67	0.60
HuN	Hunan	0.55	0.54	0.58	0.48	0.25	0.34	0.39	0.40	0.17	0.16	0.16	0.20	0.31	0.31	0.39
GD	Guangdong	0.94	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
GX	Guangxi	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
HaN	Hainan	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CQ	Chongqing	0.01	0.00	0.02	1.00	0.25	1.00	1.00	1.00	1.00	1.00	1.00	0.06	0.09	0.05	0.13
SC	Sichuan	0.00	0.00	0.15	0.22	0.19	0.31	1.00	1.00	0.26	0.16	0.08	0.03	0.08	0.12	0.17
GZ	Guizhou	1.00	1.00	0.08	1.00	0.05	1.00	0.10	0.18	0.15	0.09	0.05	0.05	0.08	0.09	0.25
YN	Yunnan	0.00	0.00	0.00	0.09	0.03	0.04	0.12	0.11	0.04	0.10	0.07	0.07	0.13	0.11	0.14
SaX	Shaanxi	1.00	1.00	1.00	1.00	0.20	0.62	0.48	0.50	0.49	0.51	0.53	0.26	0.31	0.31	0.37
GS	Gansu	1.00	1.00	1.00	0.99	0.69	0.71	0.70	0.75	0.52	0.40	0.35	0.30	0.37	0.41	0.39
QH	Qinghai	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
NX	Ningxia	1.00	1.00	1.00	1.00	1.00	1.00	0.31	0.24	1.00	1.00	0.04	0.11	0.25	0.25	1.00
XJ	Xinjiang	1.00	1.00	0.36	0.25	0.26	0.31	0.21	0.18	0.19	0.36	0.11	0.12	0.14	0.17	1.00

Table A4. Regional DDF results of *chemicals* sector. The full names of provinces refer to Table A3.

Provinces	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
BJ	0.81	0.62	0.89	1.00	0.39	0.63	0.60	0.69	0.56	0.97	0.58	0.27	1.00	1.00	1.00
TJ	0.84	0.61	0.36	0.78	0.48	0.69	0.65	0.80	0.64	0.80	0.96	0.62	1.00	1.00	1.00
HeB	0.12	0.10	0.01	0.05	0.11	0.54	0.35	0.30	0.34	0.09	0.14	0.11	0.10	0.05	0.15
SX	1.00	1.00	0.04	0.04	0.06	0.09	0.08	0.05	0.15	0.08	0.05	0.02	0.04	0.04	0.06
IM	0.05	0.05	0.32	0.09	0.19	0.61	0.21	0.29	0.26	0.09	0.21	0.03	0.99	0.05	0.16
LN	1.00	0.48	0.01	0.09	0.18	0.23	0.34	0.28	0.36	0.40	0.43	0.37	0.64	0.47	0.33
JL	0.15	0.15	0.19	0.59	0.71	0.51	0.43	0.43	0.46	0.39	0.55	0.23	0.52	0.39	0.44
HLJ	0.05	0.22	0.46	0.09	0.24	0.09	0.14	0.11	0.21	0.06	0.10	1.00	0.05	0.03	0.06
SH	1.00	1.00	1.00	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.42	1.00	1.00	1.00
JS	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ZJ	1.00	1.00	0.80	1.00	0.85	1.00	1.00	1.00	1.00	0.91	0.99	0.69	1.00	1.00	0.91
AH	0.04	0.03	0.02	0.03	0.05	0.27	0.29	0.15	0.19	0.26	0.47	0.37	1.00	0.18	0.81
FJ	0.20	0.72	0.53	1.00	0.81	1.00	1.00	0.94	1.00	0.60	0.93	0.73	0.85	0.76	0.58
JX	0.08	0.12	0.55	0.14	0.28	0.51	0.56	0.81	1.00	0.44	0.60	0.86	0.65	0.62	0.83
SD	0.76	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
HeN	0.28	0.21	0.05	0.57	0.82	0.65	0.56	0.54	0.70	0.08	0.06	0.05	0.06	0.21	0.15
HuB	0.14	0.05	0.01	0.02	0.10	0.14	0.07	0.08	0.07	0.03	0.15	0.08	0.40	0.54	0.72
HuN	0.57	0.54	0.38	0.29	0.83	0.25	0.14	0.14	0.14	0.18	0.26	0.07	0.06	0.06	1.00
GD	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
GX	0.82	0.75	1.00	0.03	0.96	0.65	0.66	0.25	0.17	0.12	0.07	0.05	0.14	0.08	0.20
HaN	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CQ	0.04	0.03	0.07	0.03	0.07	0.16	0.19	0.11	0.15	0.04	0.13	0.04	0.13	0.05	0.13
SC	0.14	0.12	0.01	0.08	0.44	0.57	0.47	0.22	0.25	0.10	0.13	0.05	0.03	0.02	0.11
GZ	0.08	0.08	0.28	0.06	0.53	0.29	0.35	0.26	0.67	0.11	0.37	0.08	0.23	0.08	0.13
YN	0.06	0.04	0.02	0.13	0.08	0.18	0.26	0.25	0.26	0.06	0.09	0.05	0.08	0.03	0.06
SaX	0.09	0.06	0.09	0.02	0.14	0.90	0.08	0.23	0.19	0.05	1.00	0.02	0.30	0.22	0.03
GS	0.36	0.36	1.00	0.12	0.27	0.33	0.62	1.00	1.00	0.14	0.14	0.03	0.16	0.09	0.05
QH	0.02	0.00	1.00	0.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.01	0.17	0.11	0.09
NX	1.00	1.00	0.65	0.02	1.00	1.00	0.45	1.00	0.89	0.25	1.00	0.05	0.20	0.25	0.08
XJ	1.00	0.25	1.00	1.00	0.42	0.23	0.12	0.06	0.97	0.01	0.01	0.01	0.01	0.01	0.01

Table A5. Regional DDF results of *non-metallic products* sector. The full names of provinces refer to Table A3.

Provinces	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
BJ	0.62	0.61	0.72	0.73	0.80	0.82	0.79	0.96	0.79	0.87	1.00	1.00	1.00	1.00	1.00
TJ	0.50	0.42	0.78	0.77	0.82	0.86	1.00	1.00	1.00	1.00	1.00	1.00	0.97	1.00	1.00
HeB	0.64	0.59	0.50	0.40	0.45	0.51	0.46	0.42	0.40	0.40	0.42	0.46	0.47	0.52	0.54
SX	0.23	0.22	0.34	0.31	0.28	0.28	0.22	0.31	0.24	0.27	0.24	0.21	0.16	0.15	0.15
IM	0.31	0.24	0.57	0.54	0.36	0.38	0.35	0.33	1.00	1.00	1.00	0.31	0.28	1.00	0.30
LN	1.00	1.00	0.71	0.45	0.67	0.79	0.81	0.88	0.95	1.00	1.00	1.00	1.00	0.98	0.65
JL	0.29	0.26	0.38	0.40	0.40	0.38	0.43	0.34	0.99	1.00	1.00	1.00	1.00	1.00	1.00
HLJ	0.21	0.16	0.30	0.31	0.26	0.26	0.24	0.27	0.29	0.31	0.28	1.00	0.29	0.24	0.39
SH	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
JS	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ZJ	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.74	0.97	0.82
AH	0.21	0.20	0.24	0.22	0.28	0.25	0.30	0.32	0.36	0.46	0.73	0.56	0.57	0.61	0.60
FJ	0.63	0.72	0.85	0.92	1.00	1.00	1.00	0.87	0.84	0.80	0.94	1.00	0.93	1.00	0.99
JX	0.22	0.19	0.33	0.27	0.28	0.30	0.32	1.00	0.40	0.47	0.51	0.54	0.54	0.56	0.55
SD	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
HeN	1.00	0.86	0.94	0.74	0.81	0.83	0.85	0.84	0.83	0.90	1.00	1.00	1.00	1.00	1.00
HuB	1.00	0.52	0.40	0.19	0.23	0.26	0.30	0.34	0.35	0.49	0.78	0.64	0.71	0.81	0.80
HuN	0.32	0.34	0.30	0.22	0.26	0.26	0.31	0.32	0.36	0.46	0.55	0.52	0.60	0.58	0.41
GD	1.00	1.00	1.00	0.97	0.97	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
GX	0.16	0.14	0.22	0.19	0.20	0.20	0.17	0.17	0.13	0.18	0.24	0.27	0.29	0.32	0.33
HaN	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CQ	0.18	0.15	0.30	0.32	0.34	0.33	0.31	0.27	0.21	0.26	0.51	0.45	0.59	0.71	0.77
SC	0.40	0.48	0.41	0.27	0.43	0.49	0.49	0.50	0.51	0.53	0.63	0.49	0.49	0.53	0.63
GZ	0.21	0.18	0.39	0.41	0.34	0.36	0.26	0.37	0.26	0.29	0.22	0.17	1.00	1.00	1.00
YN	0.21	0.18	0.33	0.33	0.24	0.26	0.20	0.21	0.14	0.16	0.15	0.19	0.18	0.22	0.16
SaX	0.22	0.23	0.38	0.38	0.31	0.32	0.24	0.25	0.19	0.18	0.15	0.27	0.38	0.69	1.00
GS	0.38	0.30	0.51	0.41	0.35	0.39	0.28	0.40	0.35	0.41	0.36	0.32	0.28	0.20	0.21
QH	0.50	0.10	0.95	0.96	0.78	0.88	1.00	0.62	1.00	1.00	1.00	0.82	0.78	1.00	0.79
NX	1.00	1.00	0.56	0.76	0.76	0.67	0.46	0.67	0.65	0.80	0.74	1.00	0.98	1.00	0.97
XJ	0.31	0.26	0.54	0.49	0.44	0.42	0.29	0.36	0.13	0.51	0.31	0.24	0.20	0.17	0.16

Table A6. Regional DDF results of *ferrous metals* sector. The full names of provinces refer to Table A3.

Provinces	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
BJ	0.85	0.47	0.48	0.61	0.83	0.82	0.80	0.96	0.90	1.00	1.00	1.00	1.00	1.00	1.00
TJ	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
HeB	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SX	0.09	0.18	0.19	0.20	0.32	0.30	0.33	0.27	0.25	0.26	0.25	0.25	0.30	0.12	0.22
IM	0.36	0.26	0.31	0.31	0.38	0.40	0.27	0.34	0.36	0.29	0.26	0.86	0.72	0.35	0.48
LN	1.00	0.86	0.58	0.63	0.65	0.62	0.46	0.49	0.50	0.55	0.58	0.60	0.57	0.41	0.29
JL	0.63	0.52	0.44	0.34	0.34	0.36	0.38	0.41	0.36	0.28	0.35	0.56	0.47	0.17	0.37
HLJ	1.00	0.13	0.36	0.26	0.26	0.23	0.21	0.22	0.21	0.16	0.16	0.19	0.15	0.06	0.05
SH	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
JS	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ZJ	0.81	0.80	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.93
AH	0.13	0.24	0.30	0.35	0.59	0.36	0.37	0.49	0.49	0.55	0.55	0.57	0.59	0.27	0.48
FJ	1.00	1.00	0.88	0.82	0.71	1.00	0.91	1.00	1.00	1.00	1.00	0.86	0.88	0.46	0.70
JX	1.00	1.00	0.37	0.28	0.44	0.35	0.26	0.30	0.27	0.32	0.32	0.34	0.27	0.11	0.21
SD	0.74	1.00	1.00	0.64	0.73	0.80	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.74	0.57
HeN	1.00	1.00	0.49	0.56	0.67	0.53	0.54	0.57	0.55	0.44	0.46	0.52	0.58	0.19	0.41
HuB	0.23	0.46	0.43	0.53	0.54	0.48	0.43	0.61	0.70	0.74	0.70	0.67	0.70	0.26	0.50
HuN	0.20	0.31	0.41	0.40	0.36	0.33	0.34	0.35	0.31	0.39	0.36	0.45	0.44	0.20	1.00
GD	1.00	0.84	0.86	0.98	1.00	1.00	1.00	1.00	0.95	1.00	1.00	0.87	1.00	0.67	0.88
GX	0.14	0.17	0.36	0.38	0.48	0.37	0.40	0.48	1.00	0.40	0.44	0.60	0.64	0.56	0.61
HaN	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CQ	0.19	0.17	0.32	0.45	0.27	0.35	0.35	0.35	1.00	0.45	0.48	0.38	0.60	0.19	0.44
SC	0.30	0.53	0.54	0.51	0.58	0.56	0.50	0.49	0.60	0.49	0.55	0.44	0.45	0.17	0.35
GZ	0.23	0.29	0.41	0.35	0.31	0.28	0.31	0.34	0.38	0.28	0.30	0.33	0.31	0.17	0.48
YN	0.13	0.08	0.22	0.44	0.21	0.25	0.20	0.27	0.29	0.29	0.26	0.30	0.36	0.15	0.25
SaX	0.11	0.03	0.39	0.37	0.35	0.45	0.34	0.41	0.31	0.25	0.83	0.32	0.32	0.14	0.39
GS	0.17	0.07	0.37	0.23	0.21	1.00	1.00	1.00	0.35	0.30	0.33	0.30	0.36	0.16	0.30
QH	0.47	0.62	0.77	0.46	0.55	0.47	0.39	0.39	1.00	0.26	0.32	0.33	0.29	0.12	0.23
NX	1.00	1.00	0.32	1.00	0.41	0.56	1.00	1.00	0.20	0.18	0.14	0.21	0.22	0.10	0.23
XJ	1.00	1.00	0.55	0.60	0.28	0.27	0.28	0.27	1.00	0.13	0.13	0.16	0.13	0.05	0.03

Table A7. Regional DDF results of *non-ferrous metals* sector. The full names of provinces refer to Table A3.

Provinces	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
BJ	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
TJ	0.72	1.00	0.93	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
HeB	0.98	1.00	1.00	0.87	0.55	0.42	0.31	0.31	0.46	0.43	0.43	0.62	0.60	0.60	0.40
SX	0.24	0.18	0.21	0.07	0.06	0.06	0.06	0.04	0.03	0.03	0.04	0.03	0.02	0.02	0.03
IM	0.01	0.23	0.49	0.46	0.19	0.13	0.54	0.86	0.72	0.67	0.64	1.00	0.82	0.84	1.00
LN	0.01	1.00	0.51	0.55	0.49	0.41	0.28	0.34	0.41	0.28	0.30	0.35	0.40	0.37	0.24
JL	0.00	0.00	0.14	0.21	0.03	0.10	0.14	0.17	0.23	0.27	0.06	0.06	0.14	0.06	0.18
HLJ	0.22	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SH	1.00	0.97	0.83	0.85	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
JS	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ZJ	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AH	0.19	0.22	0.25	1.00	0.79	1.00	0.74	0.92	0.79	1.00	1.00	1.00	1.00	0.95	1.00
FJ	0.86	1.00	0.78	0.59	0.57	0.59	0.45	0.79	0.92	0.66	0.79	0.75	0.55	1.00	1.00
JX	0.45	0.52	0.65	0.70	0.83	0.79	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SD	0.20	0.35	1.00	0.73	0.97	1.00	0.86	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
HeN	0.78	0.70	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.54	0.60	0.62	0.66
HuB	0.26	0.16	0.35	0.18	0.16	0.20	0.21	0.27	0.19	0.19	0.29	0.30	0.39	0.34	0.62
HuN	0.25	0.27	0.27	0.27	0.15	0.13	0.14	0.24	0.17	0.34	0.55	0.29	0.41	0.47	1.00
GD	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
GX	0.08	0.08	0.05	0.04	0.03	0.03	0.04	0.03	0.02	0.02	0.03	0.02	0.02	0.02	0.02
HaN	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CQ	0.25	0.25	0.26	0.53	0.47	0.46	0.40	0.31	0.29	0.15	0.15	0.16	0.19	0.58	0.39
SC	0.23	1.00	0.34	0.31	0.32	0.40	0.38	0.37	0.27	0.17	0.26	0.18	0.17	0.11	0.14
GZ	0.18	0.23	0.24	0.16	0.13	0.12	0.10	0.08	0.07	0.06	0.08	0.07	0.13	0.10	0.18
YN	0.33	0.51	0.36	0.45	0.20	0.26	0.32	0.20	0.17	0.16	0.23	0.22	0.21	0.24	0.24
SaX	0.01	0.05	0.06	0.04	0.04	0.05	0.07	0.08	0.23	0.08	1.00	0.16	0.17	0.16	0.23
GS	0.28	0.32	0.30	0.36	0.27	0.32	0.29	0.19	0.16	0.08	0.15	0.09	0.08	0.09	0.13
QH	0.48	0.80	0.53	0.69	0.70	0.31	0.30	0.35	0.10	0.31	0.16	0.30	0.35	0.28	0.42
NX	1.00	1.00	1.00	1.00	0.24	0.19	0.22	0.11	0.09	0.11	0.19	0.33	0.39	0.14	0.16
XJ	0.07	0.36	0.15	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.06	0.43	0.07	0.12

Table A8. Regional DDF results of *electricity* sector. The full names of provinces refer to Table A3.

Provinces	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
BJ	0.80	0.70	0.76	0.97	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
TJ	1.00	0.76	1.00	1.00	1.00	1.00	0.74	0.57	0.58	0.35	0.86	0.38	0.32	0.31	0.33
HeB	0.83	0.75	0.66	0.61	0.55	0.48	0.41	0.34	0.37	0.29	0.30	0.19	0.14	0.14	0.14
SX	0.50	0.44	0.44	0.36	0.25	0.21	0.18	0.15	0.14	0.10	0.10	0.09	0.09	0.09	0.09
IM	0.37	0.35	0.41	0.29	0.25	0.19	0.18	0.15	0.15	0.11	0.15	0.08	0.08	0.07	0.06
LN	0.71	0.71	0.58	1.00	0.83	0.42	0.40	0.36	0.29	0.18	0.16	0.15	0.13	0.12	0.12
JL	0.55	0.35	0.35	0.44	0.31	0.27	0.26	0.26	0.22	0.17	0.21	0.20	0.18	0.18	0.19
HLJ	0.67	0.90	0.95	0.57	0.38	0.35	0.29	0.22	0.26	0.18	0.17	0.16	0.18	0.15	0.15
SH	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
JS	1.00	1.00	1.00	0.75	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ZJ	0.84	0.80	0.81	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	0.91	0.85	0.84
AH	1.00	0.75	1.00	0.58	0.41	0.32	0.28	0.37	0.36	0.23	0.23	0.19	0.17	0.14	0.14
FJ	0.96	0.95	0.97	0.93	0.78	0.66	0.58	0.55	0.50	0.35	0.39	0.28	0.26	0.24	0.27
JX	0.56	0.84	0.76	0.65	0.52	0.45	0.39	0.37	0.38	0.27	0.26	0.27	0.25	0.24	0.23
SD	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.20	0.43	0.37	0.38
HeN	1.00	1.00	1.00	1.00	0.52	0.44	1.00	0.38	0.37	0.30	0.34	0.19	0.14	0.12	0.13
HuB	0.58	0.57	0.67	0.60	0.60	0.50	0.45	0.51	0.46	0.28	0.23	0.23	0.21	0.21	0.20
HuN	0.62	0.61	0.69	0.53	0.44	0.37	0.34	0.34	0.34	0.24	0.22	0.24	0.24	0.24	0.25
GD	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
GX	0.56	0.65	0.81	0.74	0.58	0.49	0.45	0.51	0.46	0.31	0.29	0.26	0.24	0.26	0.15
HaN	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CQ	0.40	0.44	0.69	0.69	0.60	0.50	0.46	0.43	0.43	0.32	0.38	0.44	0.43	0.40	0.42
SC	0.79	0.77	0.79	0.73	0.76	0.70	0.56	0.48	0.43	0.42	0.45	0.45	0.39	0.36	0.52
GZ	0.65	0.61	0.60	0.48	0.39	0.32	0.29	0.29	0.26	0.21	0.20	0.18	0.19	0.20	0.17
YN	0.71	0.76	1.00	1.00	0.52	0.39	0.35	0.37	0.32	0.28	0.29	0.31	0.34	0.39	0.56
SaX	0.45	0.45	0.59	0.47	0.38	0.30	0.27	0.26	0.23	0.18	1.00	0.18	0.16	0.15	0.15
GS	0.77	0.68	0.65	0.59	0.45	0.37	0.34	0.31	0.33	0.22	0.21	0.20	0.21	0.20	0.22
QH	0.83	0.76	1.00	1.00	1.00	0.91	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
NX	1.00	1.00	0.49	0.52	0.40	0.32	0.30	0.28	0.28	0.20	0.17	0.16	0.16	0.15	0.16
XJ	0.37	0.34	0.49	0.33	0.25	0.21	0.20	0.21	0.23	0.15	0.15	0.11	0.10	0.09	0.08

3. Smooth data for uncertainty analysis

This section is related to section 4.3.4 of the main text. The data set is from authors’ calculation, as explained in section 4.3.4.

Table A9. The smoothed results of CO_2 emissions per unit of output based on three-year moving average values (Unit: Mt/billion yuan). BAU means business as usual and BAT is the best available technology.

Sector	Scenario	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Electricity	BAU	1.608	1.532	1.443	1.324	1.256	1.209	1.082	0.952	0.877	0.813
	Frontier	1.125	1.098	1.040	0.894	0.779	0.737	0.649	0.542	0.470	0.430
	BAT	0.438	0.355	0.303	0.241	0.185	0.150	0.118	0.091	0.076	0.067
Ferrous metals	BAU	0.365	0.335	0.311	0.313	0.313	0.293	0.274	0.270	0.274	0.277
	Frontier	0.211	0.227	0.232	0.227	0.186	0.151	0.143	0.145	0.161	0.176
	BAT	0.105	0.098	0.098	0.103	0.099	0.092	0.091	0.091	0.093	0.094
Non-metallic products	BAU	0.535	0.461	0.396	0.354	0.326	0.307	0.287	0.257	0.229	0.206
	Frontier	0.352	0.302	0.291	0.279	0.234	0.194	0.184	0.186	0.180	0.161
	BAT	0.148	0.128	0.102	0.079	0.073	0.077	0.077	0.070	0.060	0.054
Petroleum	BAU	0.142	0.129	0.122	0.119	0.111	0.100	0.096	0.097	0.100	0.102
	Frontier	0.056	0.058	0.061	0.059	0.048	0.036	0.031	0.030	0.035	0.042
	BAT	0.024	0.019	0.018	0.017	0.014	0.011	0.012	0.015	0.019	0.021
Chemicals	BAU	0.065	0.057	0.051	0.046	0.040	0.035	0.031	0.025	0.022	0.021
	Frontier	0.033	0.031	0.027	0.020	0.016	0.016	0.015	0.011	0.007	0.006
	BAT	0.010	0.008	0.006	0.005	0.003	0.002	0.002	0.001	0.001	0.001
Non-ferrous metals	BAU	0.059	0.047	0.046	0.048	0.044	0.038	0.034	0.032	0.031	0.028
	Frontier	0.010	0.009	0.012	0.016	0.013	0.009	0.008	0.009	0.011	0.008
	BAT	0.007	0.006	0.006	0.005	0.005	0.004	0.004	0.003	0.003	0.003

4. Statistical description and correlation coefficient test of data set used in DDF

This section is related to section 4.3.5 of the main text. Table A10 shows the statistical description of data used in the DDF. Tables A11-16 indicate the correlation coefficients of input and output indicators in the DDF. In this table, bad output is CO_2 emissions (unit: $MtCO_2$/yr); good output is gross output (unit: billion yuan/yr); input 1 is labor (unit: 10^4 people/yr); input 2 is capital stock (unit: billion yuan/yr); and the input 3 is energy (unit: Mtce/yr).

Table A10. Descriptive statistics of inputs and outputs in 2001, 2005, 2010 and 2015.

		***Electricity* sector**					***Ferrous metals* sector**				
		Bad output	Good utput	Input 1	Input 2	Input 3	Bad output	Good utput	Input 1	Input 2	Input 3
2001	Max	126.2	71.9	19.2	1435.1	24.4	51.3	69.8	33.5	781.3	23.4
	Min	3.7	1.6	1.3	0. 7	0.3	0.1	0.4	0.1	0.7	0.01
	Mean	51.6	17.0	7.63	420.5	8.8	10.7	19.1	8.3	145.1	6.9
	SD	34.5	14.8	4.4	282.5	6.7	11.9	18.9	7.4	176.2	6.2
2005	Max	267.8	243.9	20.5	2371.5	37.3	148.9	275.7	39. 9	1011.4	69.3
	Min	7.5	6.2	1.6	43.2	0.8	0.1	0.8	0.2	2.0	0.04
	Mean	90.7	53. 6	8.4	825.0	14.3	23.6	62.2	9.6	245.8	14.4
	SD	66.8	51. 5	4.9	537.5	10.5	28.6	70.2	9.1	263.7	16.1
2010	Max	373.9	436.4	22.0	5825.9	58.0	259.2	589.0	54.7	2299.6	106.0
	Min	9.8	11.2	1.2	252.3	0.2	0.6	0.5	0.1	4.2	0.04
	Mean	131.2	107.0	9.2	2441.1	18.8	42.0	130.3	11.5	510.1	25.4
	SD	93.3	95.2	5.4	1325.0	13.5	49.9	146.7	11.7	523.4	27.2
2015	Max	453.9	761.2	20.4	12831.4	60.7	324.7	803.7	62.7	5484.3	126.5
	Min	14.0	24.9	1.2	850.4	1.1	0.1	1.2	0.1	8.7	0.06
	Mean	148.2	182.8	9.4	5559.4	18.2	47.5	168.5	12.5	1237.3	27.5
	SD	112.9	166.7	5.1	2911.8	14.1	63.2	200.4	13.3	1246.8	30.7

		***Non-metallic products* sector**					***Petroleum* sector**				
		Bad output	Good output	Input 1	Input 2	Input 3	Bad output	Good utput	Input 1	Input 2	Input 3
2001	Max	27.5	51.5	38.6	371.1	6.4	16.5	72.1	8.4	321.7	31.4
	Min	1.2	0.8	0.7	0.7	0.1	0.1	0.01	0.01	0.3	0.01
	Mean	10.2	13.0	13.1	94.8	2.4	2.9	15.4	2.0	73.5	6.6
	SD	7.6	14.0	10.6	80.0	1.8	3.7	16.8	2.2	83.7	8.3
2005	Max	54.7	153.0	53.8	595.5	13.9	34.3	150.3	17.3	405.0	40.0
	Min	1.8	1.2	0.8	6.4	0.3	0.1	0.02	0.01	0.3	0.1
	Mean	16.2	27.2	13.9	158.8	3.9	5.5	34.9	2.5	109.2	11.0
	SD	12.9	34.2	13.0	129.3	3.0	6.5	36.5	3.2	105.0	11. 7
2010	Max	60.9	355.5	62.1	3103.6	19.3	39.3	311.3	17.1	1289.6	68.9
	Min	3.6	4.6	1.0	29.0	0.4	0.3	1.5	0.1	21.5	0.1

	Mean	26.1	81.4	18.1	715.6	5.8	8.2	73.6	3.1	360.0	16.6
	SD	18.1	88.6	16.7	675.9	4.8	9.3	75.4	3.5	306.9	16.9
2015	Max	74.3	637.0	83.2	9213.9	71.6	47.4	569.9	11.9	2998.5	91.9
	Min	2.4	8.6	0.7	73.0	0.5	0.6	0.5	0.2	44.1	0.2
	Mean	32.7	159.6	19.8	2956.2	8.5	9.6	93.2	3.2	845.0	22.5
	SD	20.6	166.8	19.6	2303.8	12.9	10.1	108.0	3.2	706.7	24.2

		Chemicals **sector**					***Nonferrous metals*** **sector**				
		Bad output	Good utput	Input 1	Input 2	Input 3	Bad output	Good utput	Input 1	Input 2	Input 3
2001	Max	8.5	110.6	38.4	451.8	62.2	32.2	24.1	10.9	116.4	25.9
	Min	0.1	1.3	0.6	0.7	0.05	0.1	0.1	0.02	0.7	0.001
	Mean	2.6	20.7	10.6	131.0	13.4	2.1	7.8	3.6	44.8	3.1
	SD	2.1	23.7	8.4	100.3	15.3	5.9	5.8	2.6	33.5	5.7
2005	Max	16.0	286.3	44.8	1055.5	77.4	9.9	76.0	10.4	298.4	37.4
	Min	0.1	3.0	0.5	17.5	0.1	0.1	0.1	0.04	0.5	0.001
	Mean	3.7	49.1	11.3	216.9	21.2	2.0	23.2	4.4	71.5	4.1
	SD	3.6	66.5	10.2	212.6	20.0	2.4	21.4	3.2	63.4	7.6
2010	Max	23.9	748.9	65.4	2952.3	200.9	16.7	239.1	18.6	1236.2	48.8
	Min	0.1	7.9	0.4	38.8	1.2	0.2	0.1	0.02	0.1	0.001
	Mean	5.1	125.6	15.8	695.9	32.8	3.4	69.9	6.4	238.9	6.8
	SD	5.7	173.9	15.6	658.0	43.2	4.0	69.1	5.0	245.2	11.5
2015	Max	18.0	1455.2	70.4	12740.2	230.8	18.0	530.9	22.1	3326.3	67.4
	Min	0.1	18.1	0.4	53.8	1.7	0.1	0.4	0.05	0.1	0.003
	Mean	4.8	230.8	16.4	2811.7	40.4	3.6	121.8	6.8	1050.2	9.2
	SD	4.6	340.7	16.7	2981.1	53.2	4.7	125.7	5.6	969.3	16.6

Table A11. Correlation matrix of inputs and outputs in the DEA model (*Electricity* sector).

Indicators	CO_2 emissions	Gross output	Labor	Capital stock	Energy
CO_2 emissions	1.000				
Gross output	0.631*	1.000			
Labor	0.606*	0.446*	1.000		
Capital stock	0.625*	0.614*	0.431*	1.000	
Energy	0.870*	0.640*	0.682*	0.508*	1.000

* P value<0.05.

Table A12. Correlation matrix of inputs and outputs in DEA model (*Ferrous metals* sector).

Indicators	CO_2 emissions	Gross output	Labor	Capital stock	Energy
CO_2 emissions	1.000				
Gross output	0.836*	1.000			
Labor	0.904*	0.834*	1.000		
Capital stock	0.807*	0.834*	0.754*	1.000	
Energy	0.851*	0.754*	0.857*	0.789*	1.000

* P value<0.05.

Table A13. Correlation matrix of inputs and outputs in DEA model (*Nonmetallic products* sector).

Indicators	CO_2 emissions	Gross output	Labor	Capital stock	Energy
CO_2 emissions	1.000				
Gross output	0.790*	1.000			
Labor	0.813*	0.836*	1.000		
Capital stock	0.647*	0.786*	0.541*	1.000	
Energy	0.743*	0.537*	0.535*	0.508*	1.000

* P value<0.05.

Table A14. Correlation matrix of inputs and outputs in DEA model (*Petroleum* sector).

Indicators	CO_2 emissions	Gross output	Labor	Capital stock	Energy
CO_2 emissions	1.000				
Gross output	0.491*	1.000			
Labor	0.186*	0.498*	1.000		
Capital stock	0.454*	0.713*	0.555*	1.000	
Energy	0.253*	0.780*	0.580*	0.618*	1.000

* P value<0.05.

Table A15. Correlation matrix of inputs and outputs in DEA model (*Chemicals* sector).

Indicators	CO_2 emissions	Gross output	Labor	Capital stock	Energy
CO_2 emissions	1.000				
Gross output	0.355*	1.000			
Labor	0.469*	0.857*	1.000		
Capital stock	0.290*	0.835*	0.674*	1.000	
Energy	0.471*	0.851*	0.803*	0.736*	1.000

* P value<0.05.

Table A16. Correlation matrix of inputs and outputs in DEA model (*Non-ferrous metals* sector).

Indicators	CO_2 emissions	Gross output	Labor	Capital stock	Energy
CO_2 emissions	1.000				
Gross output	0.380*	1.000			
Labor	0.509*	0.825*	1.000		
Capital stock	0.289*	0.687*	0.559*	1.000	
Energy	0.693*	0.310*	0.488*	0.370*	1.000

* P value<0.05.

5. Predictions of national emissions and GDP

This section is related to the result analysis in the main text. The predictions of national emissions are based on the historical data in 2015 and their growth rates from 2016 to 2030. The future GDP is calculated using the historical data in 2016 and the growth rates from 2017 to 2030. The national emissions in 2015 and the growth rates of CO_2 emissions from 2016 to 2030 are taken from the website of IEA and Word Energy Outlook 2017 (IEA, 2017), reapectively. The data of GDP is from the China Statistic Yearbook (NBSC, 2001-2017) and its growth rates from 2017 to 2030 are collected from World Bank (World Bank, 2017).

Table A17. The predictions of national emissions and GDP.

Year	CO_2 Emissions (Million tons)	GDP (2000 constant price) (Billion Chinese Yuan)
2016	9357.75	42569.49
2017	9451.33	45464.21
2018	9545.84	48373.92
2019	9641.30	51421.48
2020	9737.71	54609.61
2021	9835.09	57776.97
2022	9933.44	61128.03
2023	10032.78	64673.46
2024	10133.10	68424.52
2025	10234.43	72393.14
2026	10336.78	76157.59
2027	10440.15	80117.78
2028	10544.55	84283.90
2029	10649.99	88666.67
2030	10756.49	93277.33

6. The differences of CO_2 emissions across regions

This section is related to section 4.4.1 of the main text.

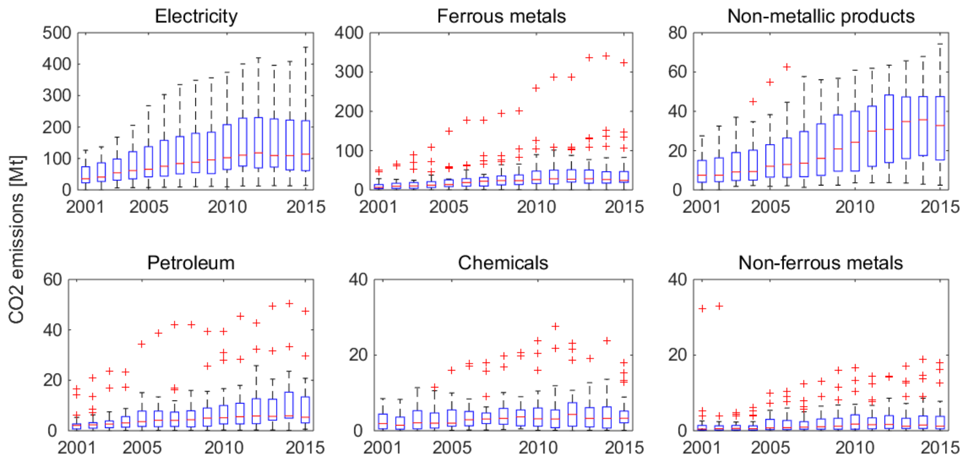

Fig. A1. The patterns of provincial CO_2 emissions of six energy-intensive sub-sectors from 2001 to 2015. Red horizontal line is the median; the upper and lower edges of the box are the 25th and 75th percentiles, respectively; the whiskers are the extreme data points without considering outliers; and the red dots are outliers.

7. The propotions of electricity generated by different technologies in 30 provinces

This section is related to section 4.5 of the main text. Following each table, there is a paragraph to describe the province selected in the frontier scenario.

Table A18. The energy mix for power generation in 2005 (Unit: %).

Provinces/Energy types	Thermal	Hydro	Nuclear	Wind	Solar
Beijing	97.80	2.20	0.00	0.00	0.00
Guangdong	77.57	9.13	13.29	0.00	0.00
Zhejiang	75.45	9.31	15.23	0.00	0.00
Fujian	62.59	37.41	0.00	0.00	0.00
Shanghai	100.00	0.00	0.00	0.00	0.00
Qinghai	25.73	74.27	0.00	0.00	0.00
Hainan	87.20	12.80	0.00	0.00	0.00
Sichuan	35.87	64.13	0.00	0.00	0.00
Tianjin	100.00	0.00	0.00	0.00	0.00
Hubei	36.92	63.08	0.00	0.00	0.00
Guangxi	56.10	43.90	0.00	0.00	0.00
Chongqing	73.40	26.60	0.00	0.00	0.00
Jiangsu	99.87	0.13	0.00	0.00	0.00
Yunnan	44.05	55.95	0.00	0.00	0.00
Jiangxi	81.83	18.17	0.00	0.00	0.00
Liaoning	93.71	6.29	0.00	0.00	0.00
Hunan	62.56	37.44	0.00	0.00	0.00
Hebei	99.58	0.42	0.00	0.00	0.00
Gansu	67.23	32.77	0.00	0.00	0.00
Anhui	98.07	1.93	0.00	0.00	0.00
Shandong	99.93	0.07	0.00	0.00	0.00
Henan	95.20	4.80	0.00	0.00	0.00

Guizhou	73.25	26.75	0.00	0.00	0.00
Heilongjiang	97.53	2.47	0.00	0.00	0.00
Shaanxi	90.75	9.25	0.00	0.00	0.00
Ningxia	94.73	5.27	0.00	0.00	0.00
Jilin	81.89	18.11	0.00	0.00	0.00
Shanxi	98.45	1.55	0.00	0.00	0.00
Inner Mongolia	98.90	1.10	0.00	0.00	0.00
Xinjiang	86.25	13.75	0.00	0.00	0.00
National	82.04	15.86	2.10	0.00	0.00

The order of provinces is based on the values of carbon intensity from the smallest to the largest. The median carbon intensity of technology frontier is from Guangxi and the reference province of best available technology is Beijing. *Sources*: China Energy Statistical Yearbook (2006-2016) (NBSC, 2006-2016).

Table A19. The energy mix for power generation in 2010 (Unit: %).

Provinces/Energy types	Thermal	Hydro	Nuclear	Wind	Solar
Beijing	97.22	1.63	0.00	1.15	0.00
Shanghai	99.73	0.00	0.00	0.25	0.01
Guangdong	78.21	10.97	10.50	0.32	0.00
Qinghai	20.75	79.25	0.00	0.00	0.00
Sichuan	31.97	68.03	0.00	0.00	0.00
Zhejiang	80.82	8.99	10.01	0.18	0.00
Fujian	65.66	33.46	0.00	0.88	0.00
Tianjin	99.98	0.00	0.00	0.02	0.00
Hubei	37.31	62.65	0.00	0.03	0.00
Guangxi	53.36	46.64	0.00	0.00	0.00
Hainan	89.72	8.71	0.00	1.57	0.00
Jiangsu	94.53	0.09	4.69	0.69	0.01
Yunnan	40.04	59.67	0.00	0.29	0.01
Chongqing	66.29	33.61	0.00	0.10	0.00
Anhui	98.69	1.31	0.00	0.00	0.00
Hunan	59.00	40.97	0.00	0.03	0.00
Jiangxi	82.06	17.73	0.00	0.21	0.00
Shandong	99.05	0.07	0.00	0.88	0.00
Hebei	96.85	0.28	0.00	2.87	0.00
Henan	95.75	4.20	0.00	0.05	0.00
Guizhou	69.94	30.06	0.00	0.00	0.00
Liaoning	92.97	3.40	0.00	3.63	0.00
Shaanxi	92.16	7.84	0.00	0.00	0.00
Gansu	63.95	33.40	0.00	2.65	0.00
Heilongjiang	92.83	2.90	0.00	4.27	0.00
Jilin	76.96	17.53	0.00	5.52	0.00
Inner Mongolia	92.14	0.67	0.00	7.18	0.00
Ningxia	95.35	3.12	0.00	1.44	0.10
Shanxi	98.04	1.71	0.00	0.26	0.00
Xinjiang	82.09	14.47	0.00	3.44	0.00
National	79.77	17.25	1.79	1.18	0.00

The order of provinces is based on the values of carbon intensity from smallest to largest. The median carbon intensity of technology frontier is from Yunnan and the reference province of best available technology is Beijing. *Sources*: China Energy Statistical Yearbook (2006-2016) (NBSC, 2006-2016).

Table A20. The energy mix for power generation in 2015 (Unit: %).

Provinces/Energy types	Thermal	Hydro	Nuclear	Wind	Solar
Beijing	97.69	1.58	0.00	0.61	0.12
Sichuan	14.17	85.47	0.00	0.33	0.04
Guangdong	72.52	10.91	15.15	1.38	0.05
Yunnan	10.48	85.66	0.00	3.63	0.22
Shanghai	99.35	0.00	0.00	0.61	0.04
Fujian	57.30	24.70	15.37	2.38	0.25
Zhejiang	74.78	7.71	16.70	0.55	0.26
Chongqing	65.56	34.13	0.00	0.31	0.00
Qinghai	21.57	64.42	0.00	1.17	12.85
Tianjin	98.96	0.03	0.00	1.01	0.00
Hunan	53.74	44.05	0.00	2.18	0.03
Hubei	41.67	57.53	0.00	0.74	0.06
Hainan	90.84	4.41	1.69	2.31	0.75
Jiangsu	94.05	0.27	3.86	1.37	0.45
Hebei	91.70	0.40	0.00	7.52	0.38
Jiangxi	80.26	18.34	0.00	1.17	0.24
Henan	95.21	4.23	0.00	0.53	0.03
Shandong	97.16	0.17	0.00	2.22	0.45
Anhui	96.41	2.40	0.00	1.01	0.18
Jilin	81.30	8.28	0.00	10.30	0.11
Shaanxi	89.51	8.27	0.00	1.72	0.50
Gansu	57.93	27.09	0.00	10.21	4.77
Liaoning	82.36	1.96	8.80	6.80	0.07
Guangxi	40.59	58.91	0.00	0.46	0.03
Heilongjiang	90.42	1.98	0.00	7.58	0.02
Guizhou	54.30	43.55	0.00	2.15	0.00
Shanxi	95.15	1.20	0.00	3.52	0.13
Ningxia	88.13	1.35	0.00	6.98	3.54
Inner Mongolia	87.22	0.93	0.00	10.40	1.45
Xinjiang	83.19	8.44	0.00	5.97	2.40
National	73.60	19.54	2.96	3.22	0.67

The order of provinces is based on the values of carbon intensity from smallest to largest. The median carbon intensity of technology frontier is from Jiangxi and the reference province of best available technology is Beijing. Sources: China Energy Statistical Yearbook (2006-2016) (NBSC, 2006-2016).

References

International Energy Agency (IEA), 2017. World Energy Outlook 2017. IEA, Paris, France <www.iea.org>.

World Bank, 2017. Global Economic Prospects. <http://www.worldbank.org/en/publication/global-economic-prospects >.

National Bureau of Statistics of China (NBSC) (2002-2017). China Statistics Yearbook. China Statistical Press, Beijing (In Chinese).

National Bureau of Statistics of China (NBSC) (2006-2016). China Energy Statistical Yearbook. China Statistical Press, Beijing (InChinese).

Chapter 5

The evolution of Chinese industrial CO_2 emissions 2000-2050: a review and meta-analysis of historical drivers, projections and policy goals[8]

Abstract: The emissions of the Chinese industrial sector alone comprise 24.1% of global emissions (7.8 $GtCyr^{-1}$ in 2015). This makes Chinese industrial emissions of unique national and international relevance in climate policy. We report a literature survey that quantitatively describes the evolution of these emissions from 2000 to 2050 in the context of policy goals. Our survey reveals that: (1) The major historical factor contributing to the decrease in industrial CO_2 emissions has been the reduction in energy intensities. However, that decrease has been more than compensated for by increases in industrial activity. (2) An ensemble of projections shows that China's industrial emissions will likely peak in 2030, in alignment with China's commitment to the Paris Agreement. The timing of the peak varies across industry sub-sectors, with *ferrous metals* and *non-metallic products* peaking first, and the *electricity* sector later. (3) The assumptions underlying optimistic scenarios broadly match the drivers of recent decreases in historical emissions (energy intensity, industrial structure and energy mix). Furthermore, these factors feature prominently in China's policy portfolio to both develop and decarbonize the Chinese industrial sector. The industrial carbon intensity targets of 2020 and 2025 are close to the median predictions in the medium scenarios from studies.

Keywords: Industrial CO_2 emissions; Historical drivers; Emission projections; Policy goals.

5.1. Introduction

Global industrial and electrical emissions have averaged 2.3% per year since 1990, with China responsible for 80% of this increase [1]. The industrial sector (which includes electricity generation, according to Chinese statistical definitions, a convention that will be followed throughout this paper) accounted for about 68% of the national energy consumption and 84% of the national CO_2 emissions in China in 2015 [2]. Given its importance, the Chinese industrial sector has been the focus of numerous national policies to improve carbon and energy efficiency. The present policy, the *China Industrial Green Development Plan* with a target year of 2020, and aims for a reduction in industrial carbon intensity (CO_2 emissions per unit of industrial value added, IVA) and energy intensity (energy consumption per unit of IVA) of 22% and 18%, respectively. The follow up *Made in China 2025* policy runs until 2025, with 40% and 34% reduction targets in carbon and energy intensities, respectively (both policies have a baseline of 2015).

Industrial CO_2 emissions exhibit many heterogeneities at regional and sub-sector levels. Labor-intensive manufacturing is concentrated in the eastern region and in industrial clusters near coastal cities, while inland provinces have developed metallurgy, mining, and other resource-intensive

[8]Chapter 5 has been submitted to Renewable & Sustainable Energy Reviews, as *Wang J., Rodrigues J.D.F., Hu M.M., Behrens P., Tukker A. The evolution of Chinese industrial CO_2 emissions 2000-2050: a review and meta-analysis of historical drivers, projections and policy goals. Renewable & Sustainable Energy Reviews (submitted in January, 2019).*

industries. Today, the four most important industrial areas are all on, or near, the coast [3]. At a sub-sectoral level, three industrial sub-sectors generate more than 80% of the total industrial emissions: *electricity* (~49%), *ferrous metals* (~20%), and *non-metallic products* (~15%). Other energy-intensive sub-sectors are *chemicals, petroleum* and *non-ferrous metals,* accounting for 4%, 2% and 1% of industrial emissions, respectively.

Given the importance of China's industrial emissions, many studies have analyzed their historical drivers and potential future trajectories. We here present the first systematic review and meta-analysis on such drivers and trajectories. We include a review of policy targets, and indicate whether these targets may be met with reference to the studies reviewed. We first present our survey method (section 5.2), then analyze drivers of emissions (section 5.3), projections (section 5.4), and policies (section 5.5). We discuss our findings in section 5.6, while section 5.7 concludes.

5.2. Method

We define the research question as "what are the driving forces and potential trajectories of industrial CO_2 emissions in China as suggested by the literature" (we follow the survey approach of Minx et al. [4]). We also analyze key sub-sectors, i.e. *electricity, ferrous metals, non-metallic products, chemical, petroleum* and *nonferrous metals*. Key words related to the research question are used to retrieve relevant literature. Here, these included: CO_2 (carbon) emissions, industrial sector (and the respective sub-sectors as classified by national statistical offices, see Table A2 and CNSA [5]), and industrial (carbon/CO_2) emissions. We used Web of Science for the search and select peer-reviewed publications in English (resulting in 271 papers). The selected papers were then screened to match the research scope. Papers related to energy consumption/intensity, consumption-based emissions, evaluation of environmental efficiency, abatement costs and quotas were excluded.

This resulted in a final selection of 135 papers, including 65 on drivers and 70 on future trajectories. We perform two meta-analyses, respectively on the driving factors of industrial emissions (9 studies out of 65 studies), and on their future trajectories (52 studies out of 70 studies). Some papers were excluded from the meta-analyses because they did not report numerical data. We compare these future trajectories to policy targets retrieved from the International Energy Agency (IEA), United Nations Framework Convention on Climate Change (UNFCCC), China's National development and Reform Commission (NDRC), China's National Energy Administration (NEA), China's Ministry of Industry and Information Technology (MIIT) as well as China's State Council (SC).

The publication date and citations for 135 papers divided into historical assessments and projections are shown in Fig. 1. There is a clear increase in publications after 2009, when China first committed to emission reductions. The five journals with most publications are: Journal of Cleaner Production (25 papers), Energy Policy (16 papers), Applied Energy (15 papers), Energy (13 papers) and Renewable & Sustainable Energy Reviews (10 papers). Table A1 of SI (Supplementary Information) presents the details of the top-10 most-cited papers.

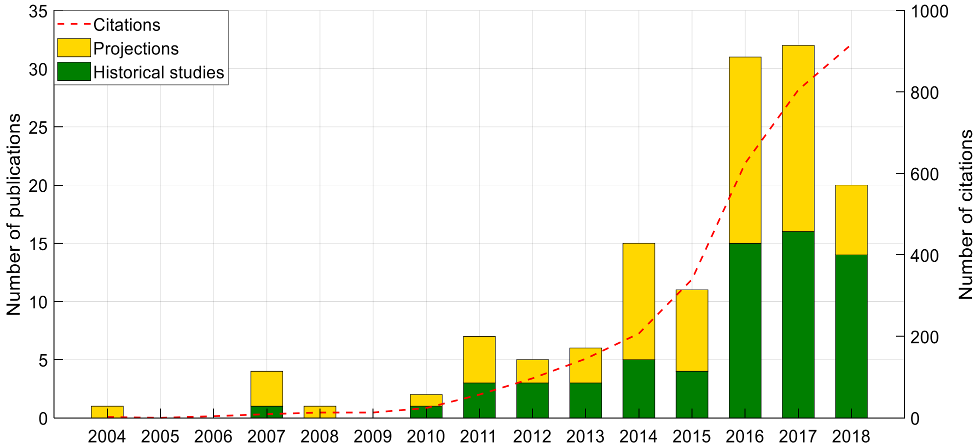

Fig. 1. Number of publications and citations in time series (status on 27 November 2018).

5.3. Reviewing the historical patterns of China's industrial CO_2 emissions

We first discuss the spatial (section 5.3.1) and sub-sectoral distribution (section 5.3.2) of historical emissions. To provide an overall perspective, we collected CO_2 emissions inventories from the China Emission Accounts and Datasets (CEADs) project. We allocated the process-emissions of cement to the *non-metallic products* sub-sector. National emissions increased from 3 $GtCO_2$/yr to 9.5 $GtCO_2$/yr between 2000 and 2013, and then decreased slightly in 2014 (9.4 $GtCO_2$/yr) and 2015 (9.3 $GtCO_2$/yr). Industrial emissions also declined in 2014 and 2015, while emissions of other sectors such as agriculture, transportation, service and households increased throughout. Section 5.3.3 reviews studies of historical drivers. Section 5.3.4 concludes in analyzing the contribution of common drivers to changes in CO_2 emissions across time.

5.3.1. The spatial/sectoral distribution of industrial emissions

Industrial emissions varied significantly across provinces due to divergences in economic and demographic trends, industrial development and population density. As shown in Fig.2, most provinces saw increased emissions from 2000 to 2015. The top three emitters, all of which are regions of major industries, were Shandong, Jiangsu and Hebei. The second group includes eight provinces: Inner Mongolia, Henan, Liaoning, Shanxi, Guangdong, Anhui, Zhejiang and Xinjiang. Some provinces are primary energy suppliers (e.g., Xinjiang, Shanxi and Inner Mongolia) and others are industrial provinces.

We calculate that China's industrial carbon intensity decreased from 0.61 to 0.45 Mt/billion yuan from 2000 to 2015 (industrial value added, 2000 constant prices, NBSC [6]). The central and northwestern provinces have higher emission intensities, whereas eastern coastal areas have lower intensities (see Figure 2). The industrial carbon intensity of Xinjiang, Ningxia, Shanxi and Gansu were the highest. Shanxi and Xinjiang are coal- and oil-rich respectively, leading to a rapid development of fossil-based industries. Conversely, developed provinces in eastern China that rely more on manufacturing had lower industrial carbon intensities, such as Jiangsu, Zhejiang and

Guangdong. In general, eastern regions dominated emissions while provinces in central and western regions exhibited higher carbon intensities [7].

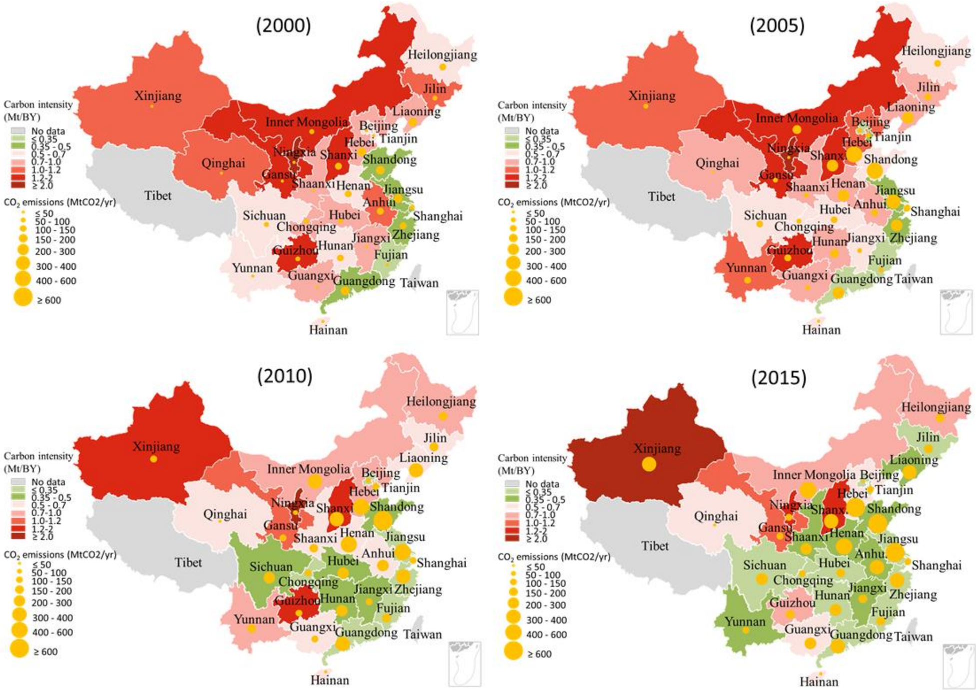

Fig. 2. The trajectories of CO_2 emissions and carbon intensity from spatial perspective. *Sources*: CO_2 emissions are from the China Emission Accounts and Datasets (CEADS) website and carbon intensity is from our calculation. Industrial value added has been converted to 2000 constant price (our calculation).

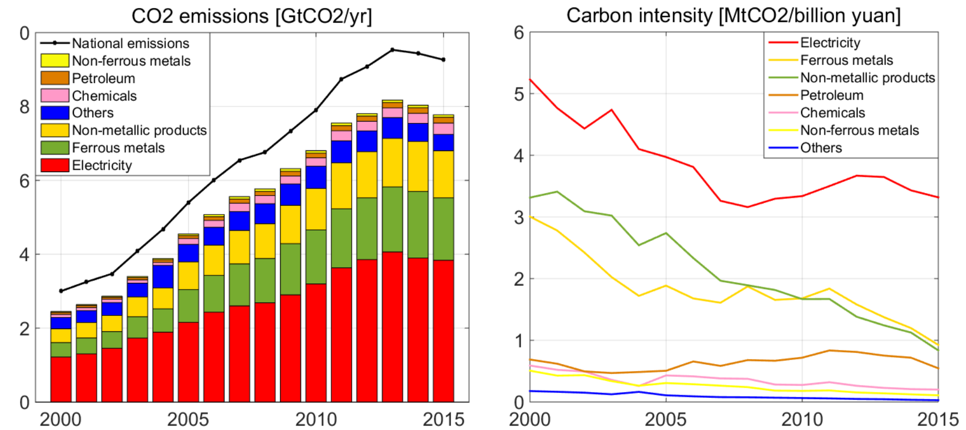

Fig. 3. The trajectories of CO_2 emissions and carbon intensity at sector level. *Sources*: CO_2 emissions are from the China Emission Accounts and Datasets (CEADS) website and carbon intensity is from our calculation. Industrial value added has been converted to the 2000 constant price (our calculation).

Along with spatial variations in industrial emissions there is a large variation across sub-sectors. The *electricity* sub-sector saw the largest emissions increase over the period of analysis accounting for almost 49% of the industry total. This was followed by *ferrous metals* and *non-metallic products* sub-sectors at 20% and 15% of the total respectively (see Fig.3). The carbon intensity of most sub-sectors showed a downward trend, except for the *petroleum* sub-sector.

5.3.2. Analysis of driving forces

We summarized the emission drivers and general findings across the literature in Tables 1, 2 and 3 (for further details see Tables A3-4 of SI). Studies based on index decomposition analysis and econometric method, which are two commonly used methods, across the literature are reviewed. The drivers analyzed include energy intensity, industrial activity, energy mix, etc. at national, regional, and sub-sector levels. Decomposition analysis captures changes in emissions between a base year and a target year, while econometric approaches identify relationships between CO_2 emissions and the drivers based on historical data (relationships are always represented as an elasticity).

Table 1. Summary of the main features across studies on drivers of CO_2 emissions/intensity (industrial sector as a whole).

Reference	Indicator	Time period	Method	Decomposition factors						
				EC	EI	IA	EM	IS	Others	Tot
Liu et al. [8]	C ↑	1998-2005	IDA	-	*-	*+	+	-		5
Chen et al.[9]	C ↑	1986-2007	IDA		*-	*+	+	+	√	5
Xu et al. [10]	C ↑	1996-2011	IDA	-	*-	*+	+	+	√	5
Liu et al. [11]	CI ↓	1996-2012	IDA	+	*-			-		3
Ouyang and Lin [12]	C ↑	1991-2010	IDA	-	*-	*+	-		√	5
Xu et al. [13]	C ↑	1995-2012	IDA		*-	*+	+	-	√	4
Zhao et al. [14]	C ↑	1993-2013	IDA	-	*-		-		√	7
Wang and Feng [15]	C ↑	2000-2015	IDA & PDA		*-	*+	+		√	7
Zhao et al. [16]	C ↑	1992-2012	IDA	-	*-	*+		+	√	5
Jiang et al. [17]	C ↑	2000-2014	IDA	-	*-	+	-			4
Wang et al. [18]	CI ↓	2006-2014	IDA & PDA	-	*-		+		√	9

Note: *C* refers to CO_2 emissions and *CI* refers to carbon intensity. *IDA* is the abbreviation of index decomposition analysis and *PDA* is production decomposition analysis. Decomposition factor, *EC*, *EI*, *IA*, *EM*, *IS*, and *others* refers to emission coefficient (CO_2 emissions/energy consumption), energy intensity (energy insumption/industrial value added), industrial activity (industrial value added, IVA), energy mix (the shares of different types of energy consumption in total consumption), industrial structure (the shares of IVA of different sub-sectors in total IVA) and other effects not listed, respectively; *Tot* means the total number of decomposition factors. √ indicates that further decomposition factors are included. "↑" means the indicator experienced an increase during the study period, and "↓" means a decrease. "+" means the effect contributed to, or was correlated with emissions increases.

"-" means the effect contributed or was correlated with decreases. The most important driver for each study is prepended with "*".

Across all studies (see Table 1), industrial activity drove emissions increases over the period of analysis. In many cases this was the largest driver of those analyzed. Similarly, across all studies energy intensity was the largest driver for reducing emissions. Changes in emission coefficients contributed to reduction of CO_2 emissions across most studies, but played a smaller role. There were no consistent results across studies for the impact of energy mix and industrial structure.

From a regional perspective (see Table 2), although the factors used in IDA and econometric studies are often different, there are some general findings across studies. On a province level the key drivers were industrial activity (GDP) causing the increase in CO_2 emissions and energy intensity leading to the decrease in industrial emissions for most regions and provinces. However, there were differences in the effects of emissions coefficient, energy intensity, industrial activity, energy mix and industrial structure across regions and provinces. For example, shifts in industrial structure instead of energy intensity were the major driver contributing to the decrease in industrial emissions for Shanghai and Henan.

Table 2. Summary of the main features across studies on drivers of CO_2 emissions/intensity (industrial sector at regional level).

Reference	Indicator	Region/Province	Time period	Method	(Decomposition) Factors						
					EC	EI	IA	EM	IS	Others	Tot
Ren et al. [19]	$C^{\#}\uparrow$	9 regions	2005-2009	IDA	-	7-,2+	+	7+,2-	+		5
Zhou et al. [20]	$C^{\#}\uparrow$	8 regions	1996-2012	IDA	4+,4-	7-,1+	7+,1-	5-,3+	+		5
Wang et al. [21]	$CI^{\#}$ 28$\downarrow$ 2$\uparrow$	30 provinces	1999-2015	IDA	20-,10+	29-, 1+		12-,18+			3
Wang and Feng [22]	$C^{\#}$ 29$\uparrow$ 1$\downarrow$	30 provinces	2000-2015	IDA		30 *-	30 *+	14-,15+		√	6
Zhao et al. [23]	C $\uparrow$	Shanghai	1996-2007	IDA	-	*-	*+		-		4
Shao et al. [24]	C $\uparrow$	Shanghai	1994-2009	IDA			+		-	√	3
Yang and Chen [25]	C $\uparrow$	Chongqing	2004-2008	IDA		-	*+	+	+		4
Deng et al. [26]	C $\uparrow$	Yunnan	1997-2012	IDA & SDA		*-	*+	-	+	√	7
Liu et al. [27]	C $\uparrow$	Henan	2001-2012	IDA		-	*+	+	*-		4
Shao et al. [28]	C $\uparrow$	Shanghai	1994-2011	IDA		-	*+	+	*-	√	7
Wu et al. [29]	C $\uparrow$	Inner Mongolia	2003-2012	IDA		-	*+	+	+	√	5
Zhang et al. [30]	CI $\downarrow$	Xinjiang	2000-2014	IDA		-		+	*+		3
Jia et al. [31]	C $\uparrow$	Nanchang	1998-2014	IDA		*-	*+	-	-	√	5
Zhao and Li [32]	C $\uparrow$	Guangdong	2000-2014	IDA		-	*+	+			3
Kang et al. [33]	C $\uparrow$	Tianjin	2001-2009	IDA	+	-	*+	+	+		5
					GDP (IVA)	IIS	P	Urb	FEM	Others	Tot
Wu et al. [34]	C	Inner Mongolia	2010-2012	Econometrics	+	-	+	+		√	5
Wu et al. [35]	C	Inner Mongolia	2011	Econometrics	+	+	+	+		√	6
Xu et al. [36]	C	Yangtze River Delta	2000-2014	Econometrics	+	-			+	√	12
Lin and Xu [37]	C^{II}	Shanghai	1960-2015	Econometrics	+,-	+,-		-,+	+, -	√	5

Note: See caption for Table 1 for definitions of all terms except where *P*, *Urb*, *IIS* and *FEM* refers to population, urbanization, share of IVA in GDP and share of fossil fuels in total energy consumption, respectively. Furthermore $C^{\#}$ refers to industrial CO_2 emissions with multi regional (provincial) details. C^{II} refers to studies where short and long-term relationships between emissions and drivers were explored.

From a sub-sector perspective, the change in industrial activity was a major driver of emissions across all sub-sectors (see Table 3). Industrial activity is often measured as industrial economic output but sometimes also as physical output. In most cases the energy intensity and the emission coefficient contributed to decreasing CO_2 emissions/intensity with energy intensity being the dominating factor. There is no unanimous finding for whether energy or industrial structure are emission drivers over this period. Econometric analyses show that GDP per capita, energy intensity, urbanization, industrialization and population all had positive (i.e., increasing) impacts on emissions for all sectors. The energy mix drove CO_2 reductions for most sectors except for *ferrous metals*. Some findings change depending on the length of the period under investigation. For example, Xu and Lin [58] explored the short-, medium- and long-term relationships between emissions and drivers in manufacturing, and found that drivers had different impacts on emissions at different stages of economic development (these results were also found by Xu and Lin [69] and may explain the lack of unanimity in other drivers more generally).

Table 3. Summary of the main features across studies on drivers of CO_2 emissions/intensity (industrial sub-sectors).

Reference	Indicator	Sector	Time period	Method	(Decomposition) Factors						
					EC	EI	IA	EM	IS	Others	Tot
Ren et al. [38]	C↑	Manufacturing	1996-2010	IDA	-	*-	*+	+	-		5
Wang et al. [39]	C↑	Energy-intensive industris	2000-2007	IDA	-	*-	*+	+			5
Wang et al. [40]	CI↓	Energy-intensive industris	1996-2014	IDA	+	*-			-		3
Jiang et al. [41]	C↑	Electricity	1996-2012	IDA		*-	+	-			3
	C↑	Non-metallic product	1996-2012	IDA		*-	+	-			3
	C↑	Ferrous metals	1996-2012	IDA		*-	+	-			3
	C↑	Petroleum	1996-2012	IDA		+	*+	+			3
	C↑	Chemicals	1996-2012	IDA		*-	+	-			3
Du et al. [42]	C↑	Ferrous metals	1986-2013	IDA		+	*+	+	-		4
	C↑	Non-ferrous metals	1986-2013	IDA		-	*+	+	+		4
	C↑	Non-metallic product	1986-2013	IDA		-	*+	+	+		4
	C↑	Petroleum	1986-2013	IDA		+	*+	+	-		4
	C↑	Chemicals	1986-2013	IDA		-	*+	+	+		4
	C↑	Electricity	1986-2013	IDA		+	*+	+	+		4
Zhang et al. [43]	C↑	Electricity	1995-2014	IDA		*-	*+	-	+	√	10
Li et al. [44]	C↑	Electricity	1990-2013	IDA	-	*+	+			√	7
Zhou et al. [45]	C↑	Electricity	2004-2010	IDA	+	*-	*+	-	+		5
Liu et al. [46]	ECI↓	Electricity	2000-2014	IDA		*-		-		√	4

Peng and Tao [47]	ECI↓	Electricity	1980-2014	IDA		*-					√	2
Wang et al. [48]	ECI↓	Electricity	1995-2014	IDA		*-		+			√	4
Yan et al. [49]	C 28↑ 2↓	Electricity	2000-2013	IDA	Almost -	13-,17+	+					3
Sun et al. [50]	C↑	Ferrous metals	1980-2008	IDA	-	*-	*+	+				4
Lin and Zhang [51]	C↑	Non-metallic product	1991-2010	IDA	-	*-	+	-	-			5
Wang et al. [52]	C↑	Non-metallic product	2005-2009	IDA	-	*-	*+	+				4
Ren and Hu [53]	C↑	Non-ferrous metals	1996-2008	IDA	-	*	*+	+				4
Shi and Zhao [54]	C↑	Non-ferrous metals	2000-2011	IDA	-	*-	+	-				4
Fan et al. [55]	C↑	Petrochemicals	2000-2010	IDA			+		-		√	3
Lin and Long [56]	C↑	Chemical	1981-2011	IDA		*-	*+	-			√	4
					GDP per capita	EI	Urb	Ind	FEM	P	Others	Tot
Lin et al. [57]	C	Manufacturing	1980-2012	Econometrics	+						√	3
Xu and Lin [58]	C^{III}	Manufacturing	1980-2014	Econometrics	-,+,-	+,+,-	-,+,+	-,-,+	-,-,+			5
Xu and Lin [59]	C	Manufacturing	2000-2013	Econometrics	+	+	+	+	-	+		6
Lin and Xu [60]	C	Manufacturing	2001-2015	Econometrics	+	+	+	+	-	+		6
Xu et al. [61]	C	Manufacturing	2000-2015	Econometrics	+		+	+	-	+	√	6
Xu and Lin [62]	C	Manufacturing	2000-2014	S-Econometrics	+	+	+	+	-	+		6
Wang et al. [63]	C	Manufacturing	2000-2013	S-Econometrics	+	+	+					3
	C	Electricity	2000-2013	S-Econometrics	+	+	+					

Zhao et al. [64]	C	Electricity	1980-2010	Econometrics	+						√	3
Yan et al. [65]	C	Electricity	1990-2014	S-Econometrics	+	+	+	+		+	√	8
Wen et al. [66]	C	Electricity	2000-2014	Econometrics	+		+	+			√	5
Yu et al. [67]	CI	Ferrous metals	1990-2010	Econometrics	+						√	3
Xu and Lin [68]	C	Ferrous metals	2000-2013	Econometrics	+	+	+	+	-			5
Xu and Lin [69]	C^{II}	Ferrous metals	1980-2013	Econometrics	+,-	-,+	+,-	-,+	+,-			5
Xu and Lin [70]	C	Ferrous metals	2000-2013	Econometrics	+	+	+	+	+			5
Xu et al. [71]	C	Ferrous metals	2000-2015	Econometrics	+	+	+	+	+	+		6

Note: See Tables 1and 2 for notes on the meaning of symbols except where S-Econometrics means the authors based themselves on the STIRPAT theory to choose the driving factors and then using the econometric method to calculate the results.

5.3.3. A meta-analysis of emission drivers in the industrial sector

The results we report so far show the general trend during the whole study period but not year-on-year changes (Table 1). Only 9 out of the 65 analyses of historical emission drivers provided numerical information on changes in the drivers over time for industrial sector as a whole (Liu et al. [8]; Chen et al. [9]; Ren et al. [38]; Xu et al. [10]; Ouyang and Lin [12]; Xu et al. [13]; Zhao et al. [14]; Wang and Feng [15]; Wang and Feng [22]). We extracted these data and show the drivers over time across the different studies (see Fig 4).

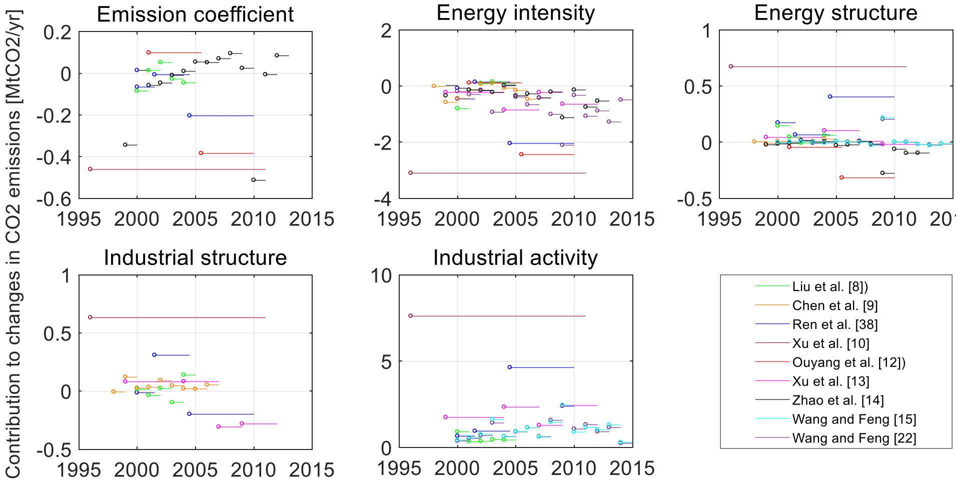

Fig. 4. Contribution of drivers to total industrial emissions. *Note*: The results of Ren et al. (2014), Xu et al. (2014b), Ouyang et al. (2015) and Xu et al. (2016) were multi-year results, others were single-year results.

Emission coefficients appear to have little effect in either increasing or decreasing emissions for single-year decompositions, though over a multi-year period there is evidence for a moderate reduction. The energy mix appears to be a driver for decreasing emissions since 2012, likely due to fuel switching. There is evidence that the ratio of coal in the sector peaked in 2010 (see Fig.A1 of SI) [2]. Additionally, there was a drop in the absolute coal consumption of the industrial sector from 2013 onward, with an average decrease of 3.5% per year from 2013 to 2015. The decrease in the dependence on coal, and its replacement by less emission intensive energy carriers such as natural gas, contributed to the decrease in industrial emissions. The large scale deployment of renewables in recent years will likely lead to further long-term emission reductions from the transitioning energy mix. Industry has also transitioned from energy-intensive to high-tech sectors over the period, with IVA in energy-intensive industries decreasing by 4.1% and in high value-added industries increasing by 6.4% from 2007 to 2015 [6]. We can see that before 2007, the industrial structure had mixed impacts on emissions, but after it began to drive decreases in emissions, suggesting that policies to drive economic transition may have been effective. Declines in emissions can be attributed to decreasing energy intensity (after 2005). Energy and industrial structure, along with energy intensity have been the major factors in decreasing industrial emissions since 2013.

5.4. Review of projections of China's industrial CO_2 emissions

5.4.1. Methods and data used to obtain projection ensembles

Future CO_2 emissions from China's industrial sector have been explored in many publications. Here we perform a meta-analysis to explore the potential range of predictions and the most robust estimates. Detailed information on the models and methods used for these projections from the literature are available in SI Tables A5-7. Approaches can be roughly divided into two categories according to data requirements and whether they are top-down (based on statistical data) or bottom-up (generally detailed energy system models) models. Top-down models have fewer technological details, but yield a more complete representation of the wider economy [72]. Model variables across both model types include all the major driving forces of emissions described previously. Scenario assumptions for all the models are outlined in full in SI Table A7.

Emission projections were extracted from 52 papers for the industrial sector and its sub-sectors (see Fig. 5). We harmonized scenario assumptions across the papers to obtain three scenarios: BAU (business-as-usual), medium and optimistic. If more than two scenarios are reported the one exhibiting highest emissions is considered BAU and the one exhibiting lowest emissions is considered optimistic. The medium scenario is obtained as the median over all other reported scenarios. If only two scenarios are reported in the original study only a BAU and optimistic scenario are considered in the meta-analysis.

5.4.2. Projections of industrial emissions

For the industrial sector as a whole, there are significant variations between projections: industrial emissions in 2030 span 6-17 $GtCO_2$/yr, depending on the scenario considered (see Fig.5): the BAU scenario spans a range of 7-17 $GtCO_2$/yr; the medium scenario 6.5-9 $GtCO_2$/yr; and the optimistic scenario 6-6.9 $GtCO_2$/yr. Median estimates in the BAU and medium scenarios generally reach an emissions peak in 2030 with values of 10 $GtCO_2$/yr and 9 $GtCO_2$/yr, respectively, while the median estimates for the optimistic scenario show a downtrend from 2015 to 2020, remain relatively stable thereafter until 2035.

The CO_2 emissions of the *electricity* sector also vary significantly in different studies, in the range of 0.5-10.6 $GtCO_2$/yr in 2050 (see Fig.5). Due to fewer data being available in 2040 and 2050, we limit our analysis to ranges in 2030: the BAU scenario spans 2.8-7.7 $GtCO_2$/yr; the medium scenario 3.5-6.9 $GtCO_2$/yr; and the optimistic scenario 1.3-6.6 $GtCO_2$/yr. The median estimate of emissions shows an increase from 2015 until 2050 in three scenarios, despite a decline in 2040. There is an outlier study which investigated the *electricity* sector: Liu et al. [73] combined the GM(1,1) model, an autoregressive integrated moving average model and a second order polynomial regression model together to forecast the CO_2 emissions from thermal power generation, indicating that CO_2 emissions will be 17.4 $GtCO_2$/yr in 2020. This result is much higher than total industrial CO_2 emissions in 2020. If we examine the historical CO_2 emissions reported in that paper, we find that the estimates of emissions from the *electricity* sector was 5.1 $GtCO_2$/yr in 2005 and almost 7 $GtCO_2$/yr in 2010, which were much higher than the official data (2.2 $GtCO_2$/yr in 2005 and 3.8 $GtCO_2$/yr in 2010) as well as the industrial total emissions (4.2 $GtCO_2$/yr in 2005 and 6.3 $GtCO_2$/yr in 2010). On the lower end, Kroeze et al. [74] obtained a much lower projection (1.6 $GtCO_2$/yr, 0.72 $GtCO_2$/yr and 0.26 $GtCO_2$/yr in 2020 under three scenarios) than others. The explanation for this low estimate may lie in the early publication date and concomitant inaccurate estimates of China's electricity consumption in recent years.

Fig.5 shows that the projections of CO_2 emissions in the *ferrous metals* sector by 2050 range from 0.6 $GtCO_2$/yr to 1 $GtCO_2$/yr. Regarding each scenario, the ranges are 0.77-1 $GtCO_2$/yr in the BAU, 0.7-0.85 $GtCO_2$/yr in the medium and 0.63-0.71 $GtCO_2$/yr in the optimistic scenario. In the three scenarios the median emissions decrease significantly from 2015 to 2050. The forecast CO_2 emissions until 2050 are lower than those in 2015 under all scenarios except for the BAU result in 2020 obtained by Wang and Lin [75]. The literature unanimously indicates that the CO_2 emissions in *ferrous metals* sector are likely to decline in the future.

The CO_2 emissions of the *non-metallic products* sector in 2050 spans 0.19-0.56 $GtCO_2$/yr, as shown in Fig.5: the BAU scenario spans 0.46-0.64 $GtCO_2$/yr; the medium scenario 0.26-0.40 $GtCO_2$/yr; and the optimistic scenario 0.19-0.24 $GtCO_2$/yr. The median emissions show a downtrend from 2015 to 2050, at which point the three scenarios exhibit values of 0.56 $GtCO_2$/yr, 0.35 $GtCO_2$/yr and 0.2 $GtCO_2$/yr respectively.

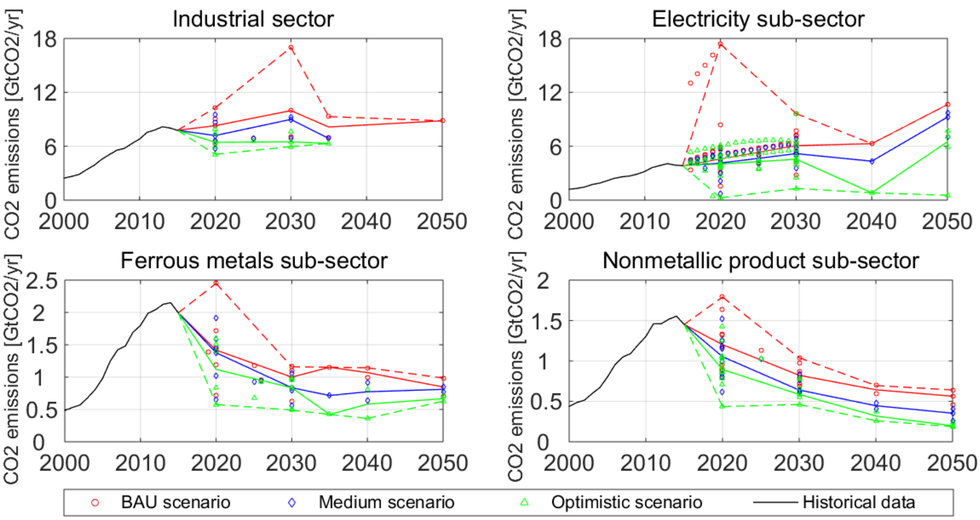

Fig. 5. Projections of CO_2 emissions in industrial sector and its major sub-sectors. The red and green dashed lines show the maximum and minimum values, respectively. The red, blue and green solid lines reflect median emissions under BAU, medium and optimistic scenarios, respectively (our calculation). The data described by circles, diamonds and triangles are from previous studies. The historical CO_2 emissions (black lines) are from the China Emission Accounts and Datasets (CEADS). Note that each sub-plot is generated from a set of different studies, hence the emissions of the industrial sector do not necessarily match the sum of the emissions of industrial sub-sectors.

Table 4. The projections of CO_2 emissions from energy-intensive industries, *chemicals*, *petroleum*, and *non-ferrous metals* sectors (unit: $GtCO_2$/yr).

Sector	Scenarios	2020	2030	References
Chemicals	BAU	1.2	-	Lin and Long [76]
	Medium scenario	0.99	-	

	Optimistic scenario	0.84	-	
	BAU	0.53	0.94	
Petroleum	Medium scenario	0.52	0.92	Xie et al. [77]
	Optimistic scenario	-	0.9	
	BAU	0.43	-	
	Medium scenario	0.4	-	Wen and Li [78]
Non-ferrous metals	Optimistic scenario	0.4	-	
	BAU	0.28	0.28	Li et al. [79]
	Optimistic scenario	0.28	0.32	
	BAU	11.5	23.6	
	Medium scenario	9.5	14.3	Lin and Tan [80]
Energy-intensive industries	Optimistic scenario	8.2	9.5	
	BAU	7.5 (2026-peak)		
	Medium scenario	7.1 (2024-peak)		Li et al. [81]
	Optimistic scenario	6.9 (2022-peak)		

The projections of CO_2 emissions in the sectors of *chemical*, *petroleum*, *nonferrous metals* and energy-intensive industries are shown in Table 4. The CO_2 emissions of the *chemical process* sector are estimated to increase to 1.2 $GtCO_2$/yr, 0.99 $GtCO_2$/yr and 0.84 $GtCO_2$/yr in 2020 in the three scenarios, respectively [76]. By 2030, the emissions of the *petroleum* sector will increase to 0.94 $GtCO_2$/yr, 0.92 $GtCO_2$/yr and 0.9 $GtCO_2$/yr [77]. The CO_2 emissions of the *non-ferrous metals* sector span 0.28-0.43 $GtCO_2$/yr in 2020, which are around those in 2015 (0.39 $GtCO_2$/yr) [78,79].

Besides the specific energy-intensive sub-sectors, the CO_2 emissions of energy-intensive industries as a whole will increase to 23.6 $GtCO_2$/yr, 14.3 $GtCO_2$/yr and 9.5 $GtCO_2$/yr in 2030 under the three scenarios [80]. However, Li et al. [81] pointed out that the CO_2 emissions peak of energy-intensive industries (coal mining and machinery manufacturing sectors are included) can be achieved under alternative scenarios in 2022 with 6.9 $GtCO_2$/yr.

5.4.3. Scenario assumptions of lowest emissions

In order to better map the best measures for achieving emissions reductions we examine the assumptions used in optimistic scenarios across papers in more detail. Since each study makes quite different assumptions, we group them by the different factors that were considered in the historical studies: emission coefficient, energy intensity, energy mix, industrial structure and industrial activity and others. Table A8 of SI reports those findings in detail, which we now summarize.

In the case of the industrial sector as a whole the most important assumptions pertain to the energy intensity factor. For example, several studies assume that energy prices increase more than has been historically observed, thus stimulating energy savings. Some studies assume that the costs of emission-reduction technologies (e.g., coke oven, sinter furnace and motor) fall much faster than under BAU scenarios. Other studies assume that energy intensity decreases faster than under BAU.

Optimistic assumptions within the *electricity* sector focus mainly on energy intensity and the energy mix. For example, some studies assume power plants have a higher efficiency than under BAU, while others assume that old, inefficient plants are decommissioned due to the adoption of new efficiency and emissions standards. Several studies also assume that the technical losses due to transmission and distribution are much lower than in the BAU. As for the energy mix in power generation, most studies assume that the fossil fuels are replaced by low-carbon energy sources, such as renewables, nuclear and natural gas.

The optimistic assumptions within the *ferrous metals* sector also focus on energy intensity. Some studies assume that energy-saving technologies improve faster than in the BAU case. For example, using international standards for advanced pulverized coal injection, a larger proportion of short-process electric arc furnace steelmaking and a higher penetration rate of energy-saving technologies.

In the *non-metallic products* sector, optimistic assumptions center on energy intensity, energy mix and industrial activity. In optimistic scenarios thermal efficiencies are usually higher, a greater proportion of fossil energy is often substituted by renewables, and in some cases, 40% of cement production is equipped with CCS. The most challenging assumptions are that cement production is one third lower than under the BAU case and that the average clinker ratio is 1/2 lower than under BAU.

For the *chemicals* sector, Lin and Long [76] assume that the lowest emissions can be achieved by higher energy efficiency and energy prices even with a higher level of industrial activity. Conversely, optimistic assumptions for the *petroleum* sector include lower emission coefficients and a lower growth rate of output even while reductions in energy intensity stagnates. For the *non-ferrous metals* sector, Li et al. [79] assume that lower growth rate in aluminum and copper output could result in lower emissions. In terms of energy-intensive industries as a whole, optimistic studies include assumptions on increasing carbon prices and faster declines in industrial output.

5.5. Policies

The Chinese Government has a tradition of frequent and strong top-down policy measures. In this section, we analyze the policies concerning climate change, energy conservation, industrial structure and energy mix enacted since 2001. As indicated in chapter 2, we reviewed policy targets set by various Chinese authorities. They are listed in Tables A9-12 of SI. In this section we introduce some of them, including the general guidelines for emission reduction at national level and specific targets for the industrial sector, and discuss the likelihood of some future targets being met.

At Copenhagen (COP15, 2009), China pledged to reduce its carbon intensity 40-45% by 2020 compared to 2005. Several energy intensity targets were also set at the same time. Perhaps most importantly, during COP21 in Paris (2015), further targets were then made for intermediate steps towards 2020, and further reductions by 2030 (reaching 60-65% reductions by 2030 on a 2005 baseline). China's Intended Nationally Determined Contribution (INDC) included a commitment to peak its CO_2 emissions by 2030, or even earlier. Climate-related policies focusing on total primary energy consumption, economic structure and energy mix are presented in Table A9 of SI.

Further targets in the industrial sector and sub-sectors were made to meet the high-level targets outlined above. The energy-saving programs targeted for the industrial sector, such as the "Different energy price scheme" in 2004, the "Top 1000 Industrial Energy Conservation Program" in 2006, the "Top 10000 Enterprises Energy Conservation and Low Carbon Action" in 2010, as well as the improvement in technologies and efficiencies of major industrial equipment, have been proved to be effective in reducing emissions through reductions in energy intensity. Recently, more specific targets have been provided for reductions in industrial emissions, we cover these next.

The number of recent targets for each sub-sector are shown in Fig.6 (a) (for more details see Tables A11-12 of SI). These targets were issued in *China's 13th Five-Year Plan*, *China Industrial Green Development Plan 2016–2020* and "*Made in China 2025*" (all targets were set against a 2015 baseline). A 22% and 40% decrease in carbon intensity was set by 2020 and 2025, respectively. The industrial energy intensity target was an 18% reduction by 2020 and 34% by 2025. Concerning the transition in industrial structure, energy-intensive industries were restricted and the share of value added in 2020 is targeted for a reduction of 2.8% from a baseline in 2015, while the share of green manufacturing in 2020 is expected to increase by 4.7%. High value-added industrial sub-sectors are incentivized and a 88% increase in the share of output value was expected in 2020. As for the shifts in energy mix, targets aim for a 3% increase in the share of low-carbon energy consumption by 2020. Regarding major sub-sectors, *ferrous metals* has a target for a 10% decrease in energy consumption and a 100-150 Mt capacity reduction in crude steel by 2020. The energy intensity of *petroleum* and *chemicals* sectors are targeted for a decrease of 18%. For *non-metallic products,* clinker capacity sees a target of 10% reduction and thermal energy intensity of clinker production 6% lower in 2020. For the *electricity* sector, beginning in 2006, there have been many policies for encouraging low-carbon power production, including targets for installed capacity of renewables and nuclear, subsidies, feed-in tariffs (FITs), and value added tax refunds (for details see Table A9 of SI). The regulations outlined in recent policy closely match the optimistic pathways for the industrial sectors and major sub-sectors as described across the literature (discussed in Section 5.4).

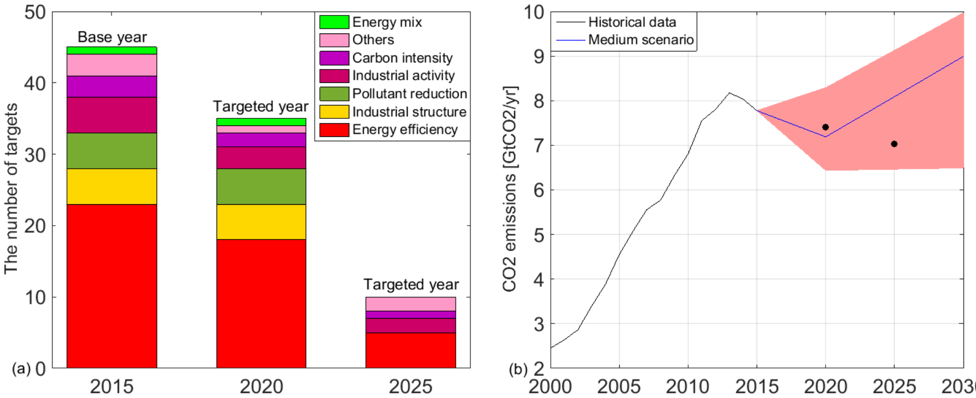

Fig. 6. (a). The number of targets for carbon-related indicators in industrial sector. (b). Comparison between targeted industrial emissions and the median emissions extracted from previous studies in three scenarios. *Note*: The solid black dots are the targeted industrial emissions in 2020 and 2025. The shadow area is limited by the median CO_2 emissions under the BAU and optimistic scenarios of the industrial sector as a whole. The blue line is the median of CO_2 emissions in medium scenario. The median CO_2 emissions under the BAU, medium and optimistic scenarios of the industrial sector are the same as in Fig.5.

We estimated the likelihood that industrial carbon intensity reduction targets are achieved in 2020 in 2025 given details from the literature and comparing the absolute emissions with projections reviewed in Section 5.4. To obtain the absolute emissions corresponding to the carbon intensity reduction targets we used the historical average growth rate of the share of IVA in GDP over the past twelve years as well as future projections of GDP (see Table A13). The projection of the share of IVA was obtained from our calculation and China's future GDP was obtained from the World Bank [82]. From this estimate we find emissions of 7.4 $GtCO_2$/yr in 2020 and 7 $GtCO_2$/yr in 2025. As shown in Fig.6 (b), the comparison of the targets with the median emissions in three scenarios considered in the meta-analysis shows that the industrial carbon intensity reduction targets lie within the range of the BAU and optimistic bounds, with the 2020 target lying above the medium scenario and the 2025 below.

5.6. Discussion

In this study we have reviewed three separate bodies of literature: historical drivers, projections and policy goals. We now discuss how these separate threads interact, the robustness of predictions, factors driving the uncertainty of historical studies and conclude with suggestions for future work.

After two decades of rapid growth in industrial CO_2 emissions (including emissions from fossil fuels and cement production), emissions decreased by 4.9% from 2013 to 2015. The decline in energy intensity, the transitioning energy mix and the shifts in industrial structure were the three major factors for this decrease.

The critical assumptions underlying the optimistic scenarios are broadly aligned with these same three factors (energy intensity, energy mix and industrial structure). Energy intensity and industrial activity feature repeatedly in optimistic scenario assumptions within industrial sub-sectors with one exception in the electricity sector where the energy mix assumptions dominate.

The energy intensity, energy mix and industrial structure, as well as other avenues for emissions reduction, are regulated by recent policies with future targets (as discussed in section 5.5). It is interesting to examine quantitatively what proportion of the legislative output these particular factors represent. The number of targets for energy efficiency (including energy intensity, technology development and green development of manufacturing), industrial structure and energy mix (excluding energy mix for power generation) accounts for 50%, 11.1% and 2.2%, respectively.

We compare CO_2 emission projections in BAU scenario from our meta-analysis with comparable numbers reported by international organizations. By 2030, the national GHG emissions (with land-use change and forestry) from three different models LIMITS-IIASA, LIMITS-PBL and LIMITS-PIK are respectively 13.21, 15.24 and 15.44 $GtCO_2$/yr [1]. IEA and EIA projections of energy-related CO_2 emissions give 10.6 $GtCO_2$/yr and 10.4 $GtCO_2$/yr, respectively [3,83]. Grubb et al. [72] reviewed the projections of China's CO_2 emissions up to 2030, indicating that BAU scenario has a range of 12-18 $GtCO_2$/yr. Our meta-analysis yields industrial median emissions of 10 $GtCO_2$/yr, which is within the potential national emissions estimated above. There is close agreement between median emissions from our meta-analysis and international estimates. For the *electricity* sector, median emissions of our meta-analysis in the BAU case is 5.9 $GtCO_2$/yr by 2030, which is well consistent with IEA's report (5.5 $GtCO_2$/yr). The comparisons indicate that the median emissions based on extensive studies are robust.

There is no official data for China's CO_2 emissions, so each study we reviewed calculates emissions themselves. An energy-related sectoral approach is commonly used. Under this approach emissions are calculated as the product of fossil fuels consumption volumes and respective emission coefficients for each type of fossil fuel, with the latter in turn calculated as the product of CO_2 emissions per net caloric value, net caloric value and oxidation ratio. Thus, the choice of energy types and emission coefficient used will cause differences in historical CO_2 estimation across studies and such differences might in turn generate uncertainties in the comparisons of emissions projections. Differences can include different methodological approaches. First, there are 30 types of energy in Energy Statistic Yearbook, but many studies used fewer. For example, Lei et al. [84] and Liu et al. [85] just considered coal consumption only. Akashi et al. [86] considered coal, oil, natural gas, biomass and electricity, while Zhou et al. [87] considered coal, electricity, liquids, gases and biomass. Uncertainties arising from energy consumption statistics also play a part in many other studies [75, 88-98]. Even though the neglected energy consumption (e.g., briquettes, gangue, naphtha and lubricants) is small, this results in the underestimation of CO_2 emissions. In addition, some studies calculated CO_2 emissions based on coal-equivalent energy consumption and the related emission factor [99,100]. Second, uncertainties are also generated by the dataset choice of emission coefficient, since both the IPCC and National Development and Reform Commission of China (NDRC) have published the calorific value and oxidation rate of energy for China [2,101]. Shan et al. [102] pointed out that there are large differences in the data published by IPCC and NDRC. Herein the IPCC data is commonly used by papers we reviewed. Since historical CO_2 emissions are always a primary input to the models for future emission scenarios and assessment for climate change, consistent energy types and appropriate emission factors are of great importance [103]. Other than the historic emissions, the models employed in different studies will also affect the projections. In this paper, the detailed advantages and disadvantages of different prediction models are not analyzed, but such a study is worthy of exploration and can be done in the future.

The meta-analysis for the projections in this paper just focused on the absolute emissions and ignored the carbon intensity since industrial intensities are comprised of many different units (e.g., CO_2/kWh, CO_2/ton steel, CO_2/ton cement), while the INDC target for intensity refers to GDP/Yuan. Future work could harmonize these units and targets in order to make a comparison if the focus is on one specific sub-sector.

5.7. Conclusion and Policy Implications

The industrial sector in China accounts for 68% of energy consumption and 84% of CO_2 emissions. In this study we reviewed the findings of 135 recent publications on this topic and provided an overview of the historical drivers and projections of industrial CO_2 emissions, in light of policy goals.

The literature on historical drivers suggests various effects on industrial CO_2 emissions. Industrial activity (monetary or physical output) was the most important driver for increasing emissions and energy intensity (i.e. efficiency improvements) was the driver for the most reductions. Shifts in industrial and energy mix showed mixed effects during the earlier period, but drove reductions in emissions after 2007 and 2012, respectively. Policies for shifting energy and industrial structure have been reinforced in recent years, so they will likely be crucial drivers for reducing future emissions.

The Paris Agreement aims to hold the average temperature well below 2 degrees above pre-industrial levels and a more ambitious target of 1.5 degrees. In the agreement, China made the commitment (INDC) to peak CO_2 emissions by 2030 or earlier. China's industrial sector comprises 84% of national emissions, so the timing of the industrial peak is closely related to the national one. According to our meta-analysis peak emissions is likely by 2030, in fact it may have already peaked (in 2013 according to the optimistic scenario). Median CO_2 emissions of the *electricity* sub-sector tend to increase until 2050. But even though electricity is the largest sub-sector, reductions in other sub-sectors compensate for this.

Recent policies are increasingly well aligned with China’s Paris commitment giving some hope that if carbon intensity targets are met then peaking emissions of the industrial sector well before 2030 may prove possible. Based on the results obtained, the recent policies for industrial sector should be well implicated, which have significant impacts on the earlier peak of industrial emissions. In spite of the direct regulations for the items related to the climate change, other national policies, such as carbon capture and storage as well as emissions trading system are also important for industrial sector to reduce its emissions.

References

[1] CAIT Climate Data Explorer. 2015. Washington, DC: World Resources Institute. Available online from: <http://cait.wri.org>.

[2] National Bureau of Statistics of China (NBSC) (2001-2016). China Energy Statistical Yearbook. China Statistical Press, Beijing (In Chinese).

[3] International Energy Agency (IEA), 2017. World Energy Outlook 2017. < https://www.iea.org/weo2017/>.

[4] Minx J., Lamb W.F., Callaghan M.W., Fuss S., Hilarire J., Creutzig F., et al. Negative emissions-Part 1: Research landscape and synthesis. Environmental Research Letters 2018; 13(6): 063001.

[5] China National Standardization Administration (CNSA), 2017. Industrial classification for national economic activities. < http://www.stats.gov.cn/tjsj/tjbz/hyflbz/201710/P020181022345132273248.pdf>.

[6] National Bureau of Statistics of China (NBSC) (2001-2016). China Statistics Yearbook. China Statistical Press, Beijing (In Chinese).

[7] Liang H.W., Dong L., Luo X., Ren J.Z., Zhang N., Gao Z.Q., Dou Y. Balancing regional industrial development: analysis on regional disparity of China's industrial emissions and policy implications. Journal of Cleaner Production 2016; 126: 223-235.

[8] Liu L.C., Fan Y., Wu G., Wei Y.M. Using LMDI method to analyzed the change of China's industrial CO_2 emissions from final fuel use: An empirical analysis. Energy Policy 2007; 35: 5892-5900.

[9] Chen L., Yang Z.F., Chen B. Decomposition Analysis of Energy-Related Industrial CO_2 Emissions in China. Energies 2013; 6: 2319-2337.

[10] Xu X., Zhao T., Liu N., Kang J. Changes of energy-related GHG emissions in China: An empirical analysis from sectoral perspective. Applied Energy 2014; 132: 298-307.

[11] Liu N., Ma Z.J., Kang J.D. Changes in carbon intensity in China's industrial sector: Decomposition and attribution analysis. Energy Policy 2015; 87: 28-38.

[12] Ouyang X.L., Lin B.Q. An analysis of the driving forces of energy-related carbon dioxide emissions in China's industrial sector. Renewable & Sustainable Energy Reviews 2015; 45: 838-849.

[13] Xu S.C., He Z.X., Long R.Y., Chen H. Factors that influence carbon emissions due to energy consumption based on different stages and sectors in China. Journal of Cleaner Production 2016; 115: 139-148.

[14] Zhao X.R., Zhang X., Shao S. Decoupling CO_2 emissions and industrial growth in China over 1993-2013: The role of investment. Energy Economics 2016; 60: 275-292.

[15] Wang M., Feng C. Understanding China's industrial CO_2 emissions: A comprehensive decomposition framework. Journal of Cleaner Production 2017; 166: 1335-1346.

[16] Zhao X., Zhang X., Li N., Shao S., Geng Y. Decoupling economic growth from carbon dioxide emissions in China: A sectoral factor decomposition analysis. Journal of Cleaner Production 2017; 142: 3500-3516.

[17] Jiang R., Zhou Y.L., Li R.G. Moving to a Low-Carbon Economy in China: Decoupling and Decomposition Analysis of Emission and Economy from a Sector Perspective. Sustainability 2018; 10(4): 978.

[18] Wang Q.W., Hang Y., Su B., Zhou P. Contributions to sector-level carbon intensity change: An integrated decomposition analysis. Energy Economics 2018; 70: 12-25.

[19] Ren S.G., Fu X., Chen X.H. Regional variation of energy-related industrial CO_2 emissions mitigation in China. China Economic Review 2012; 23: 1134-1145.

[20] Zhou X., Zhang M., Zhou M.H., Zhou M. A comparative study on decoupling relationship and influence factors between China's regional economic development and industrial energy-related carbon emissions. Journal of Cleaner Production 2017; 142: 783-800.

[21] Wang J., Hu M., Rodrigues J.F.D. An empirical spatiotemporal decomposition analysis of carbon intensity in China's industrial sector. Journal of Cleaner Production 2018; 195: 133-144.

[22] Wang M., Feng C. Using an extended logarithmicmean Divisia index approach to assess the roles of economic factors on industrial CO_2 emissions of China. Energy Economics 2018; 76: 101-114.

[23] Zhao M., Tan L.R., Zhang W.G., Ji M.H., Liu Y.A., Yu L.Z. Decomposing the influencing factors of industrial carbon emissions in Shanghai using the LMDI method. Energy 2010; 35: 2505-2510.

[24] Shao S., Yang L.L., Yu M.B., Yu M.L. Estimation, characteristics, and determinants of energy-related industrial CO_2 emissions in Shanghai (China), 1994-2009. Energy Policy 2011; 39: 6476-6494.

[25] Yang J., Chen B. Using LMDI method to analyze the change of industrial CO_2 emission from energy use in Chongqing. Frontiers of Earth Science 2011; 5: 103-109.

[26] Deng M.X., Li W., Hu Y. Decomposing Industrial Energy-Related CO_2 Emissions in Yunnan Province, China: Switching to Low-Carbon Economic Growth. Energies 2016; 9(1).

[27] Liu L., Wang S.S., Wang K., Zhang R.Q., Tang X.Y. LMDI decomposition analysis of industry carbon emissions in Henan Province, China: comparison between different 5-year plans. Natural Hazards 2016; 80: 997-1014.

[28] Shao S., Yang L.L., Gan C.H., Cao J.H., Geng Y., Guan D.B. Using an extended LMDI model to explore techno-economic drivers of energy-related industrial CO_2 emission changes: A case study for Shanghai (China). Renewable & Sustainable Energy Reviews 2016; 55: 516-536.

[29] Wu R., Zhang J., Bao Y., Lai Q., Tong S., Song Y. Decomposing the Influencing Factors of Industrial Sector Carbon Dioxide Emissions in Inner Mongolia Based on the LMDI Method. Sustainability 2016; 8(7): 661.

[30] Zhang X.L., Zhao Y., Sun Q., Wang C.J. Decomposition and Attribution Analysis of Industrial Carbon Intensity Changes in Xinjiang, China. Sustainability 2017; 9(3): 459.

[31] Jia J.S., Gong Z.H., Xie D.M., Chen J.H., Chen C.D. Analysis of drivers and policy implications of carbon dioxide emissions of industrial energy consumption in an underdeveloped city: The case of Nanchang, China. Journal of Cleaner Production 2018; 183: 843-857.

[32] Zhao M.M., Li R. Decoupling and decomposition analysis of carbon emissions from economic output in Chinese Guangdong Province: A sector perspective. Energy & Environment 2018; 29: 543-555.

[33] Kang J., Zhao T., Liu N., Zhang X., Xu X., Lin T. A multi-sectoral decomposition analysis of city-level greenhouse gas emissions: Case study of Tianjin, China. Energy 2014; 68: 562-571.

[34] Wu R.N., Zhang J.Q., Bao Y.H., Tong S.Q. Using a Geographically Weighted Regression Model to Explore the Influencing Factors of CO_2 Emissions from Energy Consumption in the Industrial Sector. Polish Journal of Environmental Studies 2016; 25: 2641-2651.

[35] Wu R.N., Zhang J.Q., Bao Y.H., Zhang F. Geographical Detector Model for Influencing Factors of Industrial Sector Carbon Dioxide Emissions in Inner Mongolia, China. Sustainability 2016; 8(2): 149.

[36] Xu X.B., Yang G.S., Tan Y., Zhuang Q.L., Tang X.G., Zhao K.Y., Wang S.R. Factors influencing industrial carbon emissions and strategies for carbon mitigation in the Yangtze River Delta of China. Journal of Cleaner Production 2017; 142: 3607-3616.

[37] Lin B.Q., Xu B. Growth of industrial CO_2 emissions in Shanghai city: Evidence from a dynamic vector autoregression analysis. Energy 2018; 151: 167-177.

[38] Ren S.G., Yin H.Y., Chen X.H. Using LMDI to analyze the decoupling of carbon dioxide emissions by China's manufacturing industry. Environmental Development 2014; 9: 61-75.

[39] Wang Z.H., Zhang B., Yin J.H. Determinants of the increased CO_2 emission and adaption strategy in Chinese energy-intensive industry. Natural Hazards 2012; 62: 17-30.

[40] Wang J., Zhao T., Zhang X.H. Changes in carbon intensity of China's energy-intensive industries: a combined decomposition and attribution analysis. Natural Hazards 2017; 88: 1655-1675.

[41] Jiang J.J., Ye B., Xie D.J., Li J., Miao L.X., Yang P. Sector decomposition of China's national economic carbon emissions and its policy implication for national ETS development. Renewable & Sustainable Energy Reviews 2017; 75: 855-867.

[42] Du G., Sun C.W., Ouyang X.L., Zhang C. A decomposition analysis of energy-related CO_2 emissions in Chinese six high-energy intensive industries. Journal of Cleaner Production 2018; 184: 1102-1112.

[43] Zhang C.Q., Zhang M., Zhang N. CO_2 Emissions from the Power Industry in the China's Iteijing-Tianjin-Hebei Region: Decomposition and Policy Analysis. Polish Journal of Environmental Studies 2017; 26: 903-916.

[44] Li X.Z., Liao H., Du Y.F., Wang C., Wang J.W., Liu Y.A. Carbon dioxide emissions from the electricity sector in major countries: a decomposition analysis. Environmental Science and Pollution Research 2018; 25: 6814-6825.

[45] Zhou G., Chung W., Zhang Y. Carbon dioxide emissions and energy efficiency analysis of China's regional thermal electricity generation. Journal of Cleaner Production 2014; 83: 173-184.

[46] Liu N., Ma Z., Kang J. A regional analysis of carbon intensities of electricity generation in China. Energy Economics 2017; 67: 268-277.

[47] Peng X., Tao X.M.. Decomposition of carbon intensity in electricity production: Technological innovation and structural adjustment in China's power sector. Journal of Cleaner Production 2018; 172: 805-818.

[48] Wang J.F., He S.T., Qiu Y., Liu N., Li Y.J., Dong Z.F. Investigating driving forces of aggregate carbon intensity of electricity generation in China. Energy Policy 2018; 113: 249-257.

[49] Yan Q., Wang Y., Baležentis T., Sun Y., Streimikiene D. Energy-Related CO_2 Emission in China's Provincial Thermal Electricity Generation: Driving Factors and Possibilities for Abatement. Energies 2018; 11(5): 1096.

[50] Sun W.J., Cai J.J., Mao H.J., Guan D.J. Change in Carbon Dioxide (CO_2) Emissions From Energy Use in China's Iron and Steel Industry. Journal of Iron and Steel Research, International 2011; 18: 31-36.

[51] Lin B.Q., Zhang Z.H. Carbon emissions in China's cement industry: A sector and policy analysis. Renewable & Sustainable Energy Reviews 2016; 58: 1387-1394.

[52] Wang Y.L., Zhu Q.H., Geng Y. Trajectory and driving factors for GHG emissions in the Chinese cement industry. Journal of Cleaner Production 2013; 53: 252-260.

[53] Ren S.G., Hu Z. Effects of decoupling of carbon dioxide emission by Chinese nonferrous metals industry. Energy Policy 2012; 43: 407-414.

[54] Shi Y., Zhao T. A decomposition analysis of carbon dioxide emissions in the Chinese nonferrous metal industry. Mitigation and Adaptation Strategies for Global Change 2016; 21: 823-838.

[55] Fan TJ, Luo RL, Xia HY, Li XP. Using LMDI method to analyze the influencing factors of carbon emissions in China's petrochemical industries. Natural Hazards 2015; 75: 319-332.

[56] Lin B.Q., Long H.Y. Emissions reduction in China's chemical industry - Based on LMDI. Renewable & Sustainable Energy Reviews 2016; 53: 1348-1355.

[57] Lin B.Q., Moubarak M., Ouyang X.L. Carbon dioxide emissions and growth of the manufacturing sector: Evidence for China. Energy 2014; 76: 830-837.

[58] Xu B., Lin B.Q. Reducing carbon dioxide emissions in China's manufacturing industry: a dynamic vector autoregression approach. Journal of Cleaner Production 2016; 131: 594-606.

[59] Xu B., Lin B.Q. Reducing CO_2 emissions in China's manufacturing industry: Evidence from nonparametric additive regression models. Energy 2016; 101: 161-173.

[60] Lin B.Q., Xu B. Which provinces should pay more attention to CO_2 emissions? Using the quantile regression to investigate China's manufacturing industry. Journal of Cleaner Production 2017; 164: 980-993.

[61] Xu B., Xu L., Xu R.J., Luo L.Q. Geographical analysis of CO_2 emissions in China's manufacturing industry: A geographically weighted regression model. Journal of Cleaner Production 2017; 166: 628-640.

[62] Xu R.J., Lin B.Q. Why are there large regional differences in CO_2 emissions? Evidence from China's manufacturing industry. Journal of Cleaner Production 2017; 140: 1330-1343.

[63] Wang Y., Zhang C., Lu A.T., Li L., He Y.M., ToJo J.J., Zhu X.D. A disaggregated analysis of the environmental Kuznets curve for industrial CO_2 emissions in China. Applied Energy 2017; 190: 172-180.

[64] Zhao X.L., Ma Q., Yang R. Factors influencing CO_2 emissions in China's power industry: Co-integration analysis. Energy Policy 2013; 57: 89-98.

[65] Yan D., Lei Y.L., Li L. Driving Factor Analysis of Carbon Emissions in China's Power Sector for Low-Carbon Economy. Mathematical Problems in Engineering 2017; 4954217.

[66] Wen L., Yan F., Li Y. Analysis of Influencing Factors of CO_2 Emissions in China's Power Industry and Policy Implications. Polish Journal of Environmental Studies 2018; 27: 373-382.

[67] Yu B., Li X., Qiao Y.B., Shi L. Low-carbon transition of iron and steel industry in China: Carbon intensity, economic growth and policy intervention. Journal of Environmental Sciences 2015; 28: 137-147.

[68] Xu B., Lin B.Q. Regional differences in the CO_2 emissions of China's iron and steel industry: Regional heterogeneity. Energy Policy 2016; 88: 422-434.

[69] Xu B., Lin B.Q. Assessing CO_2 emissions in China's iron and steel industry: A dynamic vector autoregression model. Applied Energy 2016; 161: 375-386.

[70] Xu B., Lin B.Q. Assessing CO_2 emissions in China's iron and steel industry: A nonparametric additive regression approach. Renewable & Sustainable Energy Reviews 2017; 72: 325-337.

[71] Xu R.J., Xu L., Xu B. Assessing CO_2 emissions in China's iron and steel industry: Evidence from quantile regression approach. Journal of Cleaner Production 2017; 152: 259-270.

[72] Grubb M., Sha F., Spencer T., Hughes N., Zhang Z.X., Agnolucci P. A review of Chinese CO_2 emission projections to 2030: the role of economic structure and policy. Climate Policy 2015; 15: S7-S39.

[73] Liu L.W., Zong H.J., Zhao E.D., Chen C.X., Wang J.Z. Can China realize its carbon emission reduction goal in 2020: From the perspective of thermal power development. Applied Energy 2014; 124: 199-212.

[74] Kroeze C., Vlasblom J., Gupta J., Boudri C., Blok K. The power sector in China and India: greenhouse gas emissions reduction potential and scenarios for 1990-2020. Energy Policy 2004; 32: 55-76.

[75] Wang X.L., Lin B.Q. How to reduce CO_2 emissions in China's iron and steel industry. Renewable & Sustainable Energy Reviews 2016; 57: 1496-1505.

[76] Lin B.Q., Long H.Y. Promoting carbon emissions reduction in China's chemical process industry. Energy 2014; 77: 822-830.

[77] Xie X., Shao S., Lin B.Q. Exploring the driving forces and mitigation pathways of CO_2 emissions in China's petroleum refining and coking industry: 1995-2031. Applied Energy 2016; 184: 1004-1015.

[78] Wen Z.G., Li H.F. Analysis of potential energy conservation and CO_2 emissions reduction in China's non-ferrous metals industry from a technology perspective. International Journal of Greenhouse Gas Control 2014; 28: 45-56.

[79] Li M.J., Mi Z.F., Coffman D., Wei Y.M. Assessing the policy impacts on non-ferrous metals industry's CO_2 reduction: Evidence from China. Journal of Cleaner Production 2018; 192: 252-261.

[80] Lin B.Q., Tan R.P. Sustainable development of China's energy intensive industries: From the aspect of carbon dioxide emissions reduction. Renewable & Sustainable Energy Reviews 2017; 77: 386-394.

[81] Li W., Lu C., Ding Y., Zhang Y.W. The impacts of policy mix for resolving overcapacity in heavy chemical industry and operating national carbon emission trading market in China. Applied Energy 2017; 204: 509-524.

[82] World Bank, 2018. Available from: < https://data.worldbank.org.cn/indicator/NV.IND.TOTL.ZS?locations=CN.>

Energy Information Administration (EIA), 2017. International Energy Outlook. Available from: < https://www.eia.gov/outlooks/ieo/pdf/ieotab_10.pdf >.

[83] Lei Y., Zhang Q., Nielsen C., He K. An inventory of primary air pollutants and CO_2 emissions from cement production in China, 1990-2020. Atmospheric Environment 2011; 45: 147-154.

[84] Liu X.B., Fan Y.B., Wang C. An estimation of the effect of carbon pricing for CO_2 mitigation in China's cement industry. Applied Energy 2017; 185: 671-686.

[85] Akashi O., Hanaoka T., Matsuoka Y., Kainuma M. A projection for global CO_2 emissions from the industrial sector through 2030 based on activity level and technology changes. Energy 2011; 36: 1855-1867.

[86] Zhou S., Kyle G.P., Yu S., Clarke L.E., Eom J., Luckow P., Chaturvedi V., Zhang X.L., Edmonds J.A. Energy use and CO_2 emissions of China's industrial sector from a global perspective. Energy Policy 2013; 58: 284-294.

[87] An R., Yu B., Li R., Wei Y.M. Potential of energy savings and CO_2 emission reduction in China’s iron and steel industry. Applied Energy 2018; 226: 862-880.

[88] Cai W.J., Wang C., Chen J.N., Wang K., Zhang Y., Lu X.D. Comparison of CO_2 emission scenarios and mitigation opportunities in China's five sectors in 2020. Energy Policy 2008; 36: 1181-1194.

[89] Chen W.Y., Yin X., Ma D. A bottom-up analysis of China's iron and steel industrial energy consumption and CO_2 emissions. Applied Energy 2014; 136: 1174-1183.

[90] Gao T.M., Shen L., Shen M., Liu L.T., Chen F.N., Gao L. Evolution and projection of CO_2 emissions for China's cement industry from 1980 to 2020. Renewable & Sustainable Energy Reviews 2017; 74: 522-537.

[91] Ke J., Zheng N., Fridley D., Price L., Zhou N. Potential energy savings and CO_2 emissions reduction of China's cement industry. Energy Policy 2012; 45: 739-751.

[92] Li N., Ma D., Chen W.Y. Quantifying the impacts of decarbonisation in China's cement sector: A perspective from an integrated assessment approach. Applied Energy 2017; 185: 1840-1848.

[93] Wang K., Wang C., Lu X.D., Chen J.N. Scenario analysis on CO_2 emissions reduction potential in China's iron and steel industry. Energy Policy 2007; 35: 2320-2335.

[94] Wei P.B., Cui H.R., Gang M.Q. Scenario analysis of energy conservation and CO_2 emissions reduction policies in China's iron and steel sector. Polish Journal of Environmental Studies 2017; 26: 2307-2317.

[95] Wen Z.G., Chen M., Meng F.X. Evaluation of energy saving potential in China's cement industry using the Asian-Pacific Integrated Model and the technology promotion policy analysis. Energy Policy 2015; 77: 227-237.

[96] Wen Z.G., Meng F.X., Chen M. Estimates of the potential for energy conservation and CO_2 emissions mitigation based on Asian-Pacific Integrated Model (AIM): the case of the iron and steel industry in China. Journal of Cleaner Production 2014; 65: 120-130.

[97] Lin B.Q., Ouyang X.L. Analysis of energy-related CO_2 (carbon dioxide) emissions and reduction potential in the Chinese non-metallic mineral products industry. Energy 2014; 68: 688-697.

[98] Zhang Q., Li Y., Xu J., Jia G.Y. Carbon element flow analysis and CO_2 emission reduction in iron and steel works. Journal of Cleaner Production 2018; 172: 709-723.

[99] Zhu B., Zhou W.J., Hu S.Y., Li Q.A., Griffy-Brown, C., Jin, Y. CO_2 emissions and reduction potential in China's chemical industry. Energy 2010; 35: 4663-4670.

[100] The Intergovernmental Panel on Climate Change (IPCC), 2006. 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Institute for Global Environmental Strategies (IGES), Hayama, Kanagawa, Japan.

[101] Shan Y.L., Guan D.B., Zheng H.R., Ou J.M., Li Y., Meng J., Mi Z.F., Liu Z., Zhang Q. Data descriptor: China CO_2 emission accounts 1997-2015. Scientific Data 2018. DOI: 10.1038/sdata.2017.201.

[102] Guan D.B., Liu Z., Geng Y., Lindner S., Hubacek K. The gigatonne gap in China's carbon dioxide inventories. Nature Climate Change 2012; 2: 672-675.

Supplementary Information

The Supplementary Information (SI) provides additional information on: (1) detailed information of the top ten cited papers. (2) classification of industrial sub-sectors; (3) detailed information, including authors, methods, study periods and drivers of studies focusing on the drivers of CO_2 emissions in the industrial sector at different levels; (4) detailed information, including authors, methods, study periods, main outcomes and scenario assumptions of studies focusing the projections of CO_2 emissions in the industrial sector and its major sub-sectors; (5) policies related to the climate change, energy conservation, energy efficiency, industrial structure and energy structure.

1. Information of top ten cited papers

We reviewed 135 studies in total, of which the detailed information of the top-10 cited papers were summarized, see Table A1. This section is related to the section 5.2 of the main body.

Table A1. Overview of top-10 most cited articles related to driving forces of industrial emissions in China.

References	Sector	Region	Method	Study period	Outcome	Citations
[1] Liu et al. (2007)	Industrial sector	China	LMDI	1998-2005	The major contributors were the industrial activity (increase) and energy intensity (decrease). The structural shift had no clear trend, and the energy structure increased industrial emissions.	232
[73] Lei et al. (2011)	Cement	China	Bottom-up model	1990-2020	It is possible to reduce CO_2 emissions from the cement sector by approximately 12.8% if advanced energy-related technologies are implemented.	147
[67] Wang et al. (2007)	Iron & Steel	China	LEAP	2000-2030	The CO_2 abatement can be reduced with recent policies and new policies, and more obvious in latter case. The shift in industrial structure and technology improvement will play important roles in emissions reduction in the future.	131
[2] Zhao et al. (2010)	Industrial sector	Shanghai	LMDI	1996-2007	The industrial output was the main driver for the increase in industrial CO_2 emissions. The decline in energy intensity was responsible for the decrease in industrial CO_2 emissions, accounting for 90% of the reduction.	120
[68] Cai et al. (2007)	Electricity	China	LEAP	2000-2030	The CO_2 emissions in China's electricity sector will increase	115

					rapidly in all scenarios until 2030. However, with the energy structure adjustment and technical mitigation measures, emissions abatement can be achieved.	
[77] Hasanbeigi et al. (2013)	Iron & Steel	China	Bottom-up electricity Conservation Supply Curve	2010-2030	More CO_2 emissions can be reduced with technical fuel savings than cost-effective way.	107
[70] Cai et al. (2008)	Industrial sub-sectors	China	LEAP	2000-2020	The CO_2 emissions can be reduced through the current sustainable development strategy and even more aggressive emission reduction policies.	91
[50] Chen et al. (2014)	Iron & Steel	China	A system dynamics model and a bottom-up energy system model-TIMES	2010-2050	With the deployment of energy conservation technologies, carbon intensity of the iron & steel sector will decrease. In the near future, the decline in carbon intensity will rely more on energy efficiency improvements; however, from a long-term perspective, structural change will be of great significance.	81
[9] Ouyang et al. (2015)	Industrial sector	China	LMDI & Cointegration method	1991-2010	Industrial activity was the major factor contributing to the increase in industrial CO_2 emissions while energy intensity is the major contributor to decrease the CO_2 emissions. There is a long-run relationship between industrial CO_2 emissions and carbon intensity of energy use, industrial value added, labor productivity and fossil fuel consumption.	79
[10] Wang et al. (2013)	Cement	China	LMDI	2005-2009	The major factors responsible for the increase in GHG emissions during 2005-2009 include the cement production activity and the clinker production activity, while the energy intensity played a positive role in decreasing GHG emissions.	72

2. Classification of industrial sub-sectors

The national statistical offices divide the industrial sector into 41 sub-sectors (CNSA, 2017). In this paper, just 40 sub-sectors were analyzed excluding Support Activities for Mining sector because the data of this sector started to be published after 2012. (sector classification see Table A5 of SI). This section supports the section 5.3.1 (sectoral distribution) of the main body.

Table A2. Classification of China's industrial sector according to the National Standard of Industrial Classification (GB/T4754) in 2017.

Code	Sub-sectors	Code	Sub-sectors
S_1	Coal mining and washing	S_{21}	Chemical materials
S_2	Oil and gas extraction	S_{22}	Pharmaceutical manufacturing
S_3	Ferrous metals mining	S_{23}	Chemical fiber
S_4	Non-ferrous metals mining	S_{24}	Rubber products
S_5	Non-metallic mineral extraction and mining	S_{25}	Plastic products
S_6	Other minerals mining and dressing	S_{26}	Non-metallic mineral products
S_7	Logging and transport of wood and bamboo	S_{27}	Ferrous metals
S_8	Agro food processing	S_{28}	Non-ferrous metals
S_9	food manufacturing	S_{29}	Metal products
S_{10}	Beverage manufacturing	S_{30}	General equipment manufacturing
S_{11}	Tobacco products	S_{31}	Special equipment
S_{12}	Textile	S_{32}	Transportation equipment
S_{13}	Textiles and clothing manufacturing	S_{33}	Electrical machinery and equipment
S_{14}	Leather, fur, and feather	S_{34}	Communication and electronic equipment
S_{15}	Wood processing and wood products	S_{35}	Instrumentation and culture-office machinery
S_{16}	Furniture manufacturing	S_{36}	Other manufacturing
S_{17}	Paper products	S_{37}	Scrap and waste
S_{18}	Printing and recording media	S_{38}	Electricity and heat production and supply
S_{19}	Stationery and sporting goods manufacturing	S_{39}	Gas production and supply
S_{20}	Petroleum, coking and nuclear fuel processing	S_{40}	Water production and supply

3. Detailed information on studies related to driving forces

The driving forces of CO_2 emissions in industrial sector at national, regional and sectoral levels were reviewed. Herein, the emissions just include the combustion of final energy consumption. There were 65 papers were selected based on the decomposition analysis and econometric method. The authors, journals, study periods, methods and drivers were summarized in Tables A3-4. This section is related to sections 5.3.2 and 5.3.3 of the main body. Fig. A1 shows the energy structure of industrial sector, which is used to support section 5.3.3 of the main body.

Table A3. Detailed information of studies on driving forces of CO_2 emissions.

ID	References	Journal	Sectors	Study period	Method
[1]	Liu et al. (2007)	Energy Policy	Industrial sector	1998-2005	LMDI
[2]	Zhao et al. (2010)	Energy	Industrial sector (Shaihai)	1996-2007	LMDI
[3]	Shao et al. (2011)	Energy Policy	Industrial sector (Shaihai)	1994-2009	STIRPAT model & LMDI
[4]	Sun et al. (2011)	Journal of Iron and Steel Research, International	Iron & steel sector	1980-2008	LMDI
[5]	Yang and Chen (2011)	Frontiers of Earth Science	Industrial sector (Chongqing)	2004-2008	LMDI
[6]	Ren and Hu (2012)	Energy Policy	Non-ferrous metals sector	1996-2008	Decomposition & Decoupling
[7]	Ren et al. (2012)	China Economic Review	Industrial sector (Regional)	2005-2009	LMDI
[8]	Wang et al. (2012)	Natural Hazards	Energy-intensive industries	2000-2007	LMDI
[9]	Chen (2013)	Energies	Industrial sector	1986-2007	LMDI
[10]	Wang et al. (2013)	Journal of Cleaner Production	Cement sector	2005-2009	LMDI
[11]	Zhao et al. (2013)	Energy Policy	Electricity sector	1980-2010	Autoregressive-distributed lag (ARDL) co-integration model
[12]	Lin et al. (2014)	Energy	Manufacturing industry	1980-2012	ARDL (autoregressive distributed lag) bounds testing & cointegration analysis
[13]	Ren et al. (2014)	Environmental Development	Manufacturing industry	1996-2010	LMDI & Decoupling analysis
[14]	Xu et al. (2014)	Applied Energy	Industrial sector	1996-2011	LMDI
[15]	Zhou et al. (2014)	Journal of Cleaner Production	Electricity sectorl	2004-2010	LMDI
[16]	Fan et al. (2015)	Natural Hazards	Petrochemical sector	2000-2010	LMDI
[17]	Liu et al. (2015)	Energy Policy	Industrial sector	1996-2012	LMDI&Attribution analysis
[18]	Ouyang and Lin(2015)	Renewable and Sustainable Energy	Industrial sector	1991-2010	LMDI

		Reviews			
[19]	Yu et al. (2015)	Journal of Environemntal Science	Iron & steel sector	1990-2010	Vector autoregression (VAR)
[20]	Deng et al. (2016)	Energies	Industrial sector (Yunnan)	1997-2012	SDA & LMDI
[21]	Lin and Long (2016)	Renewable & Sustainable Energy Reviews	Chemical sector	1981-2011	LMDI
[22]	Lin and Zhang(2016)	Renewable and Sustainable Energy Reviews	Cement sector	1991-2010	LMDI
[23]	Liu et al. (2016)	Natural Hazards	Industrial sector (Henan)	2001-2012	LMDI
[24]	Shao et al. (2016)	Renewable & Sustainable Energy Reviews	Industrial sector (Shanghai)	1994-2011	LMDI
[25]	Shi and Zhao (2016)	Mitigation and adaption strategies for global change	Non-ferrous metals sector	2000-2011	LMDI
[26]	Wu et al. (2016)	Sustainability	Industrial sector (Inner Mongolia)	2003-2012	LMDI
[27]	Wu et al. (2016)	Polish Journal of Environmental Studies	Industrial sector (Inner Mongolia)	2010-2012 (Panel data)	Geographically weighted regression model (GWR) & Geographical information systems (GIS)
[28]	Wu et al. (2016)	Sustainability	Industrial sector (Inner Mongolia)	2011	Geographical detector model
[29]	Xu and Lin. (2016)	Journal of Cleaner Production	Manufacturing industry	1980-2014	A dynamic vector autoregression approach
[30]	Xu and Lin. (2016)	Energy	Manufacturing industry	2000-2013	Nonparametric additive regression models
[31]	Xu and Lin. (2016)	Energy Policy	Iron & steel sector	2000-2013	Econometric
[32]	Xu and Lin. (2016)	Applied Energy	Iron & steel sector	1980-2013	A dynamic vector autoregression model
[33]	Xu et al. (2016)	Journal of Cleaner Production	Industrial sector	1995-2012	LMDI method

[34]	Zhao et al. (2016)	Energy Economics	Industrial sector	1993-2013	LMDI & Decoupling analysis
[35]	Jiang et al. (2017)	Renewable and Sustainable Energy Reviews	Energy-intensive industries	1996-2012	LMDI
[36]	Lin and Xu. (2017)	Journal of Cleaner Production	Manufacturing industry	2001-2015	Quantile regression approach
[37]	Liu et al. (2017)	Energy Economics	Electricity sector-Regional	2000-2014	LMDI & Attribution analysis
[38]	Wang et al. (2017)	Natural Hazards	Energy-intensive industries	1996-2014	LMDI & Atrribution analysis
[39]	Wang and Feng. (2017)	Journal of Cleaner Production	Industrial sector	2000-2015	IDA & Production-theoretical decomposition analysis (PDA)
[40]	Wang et al. (2017)	Applied Energy	Industrial sector	2000-2013	STIRPAT & Environmental Kuznets curve
[41]	Xu and Lin. (2017)	Renewable and Sustainable Energy Reviews	Iron & steel sector	2000-2013	Nonparametric additive regression models
[42]	Xu et al. (2017)	Journal of Cleaner Production	Manufacturing industry	2000-2015	A geographically weighted regression model
[43]	Xu and Lin. (2017)	Journal of Cleaner Production	Manufacturing industry	2000-2014	STIRPAT model
[44]	Xu et al. (2017)	Journal of Cleaner Production	Iron & steel sector	2000-2015	Quantile regression approach
[45]	Xu et al. (2017)	Journal of Cleaner Production	Industrial sector (Yangtze River Delta)	2000-2014	Panel regression model
[46]	Yan et al. (2017)	Mathematical Problems in Engineering	Electricity sector	1990-2014	STIRPAT
[47]	Zhang et al. (2017)	Polish Journal of Environmental Studies	Electricity sector (Beijing-Tianjin-Hebei)	1995-2014	LMDI
[48]	Zhang et al. (2017)	Sustainability	Industrial sector (Xinjiang)	2000-2014	Decomposition & Attribution analysis
[49]	Zhao et al. (2017)	Journal of Cleaner Production	Economic sectors including industrial	1992-2012	LMDI

			sector		
[50]	Zhou et al. (2017)	Journal of Cleaner Production	Industrial sector (Regional level)	1996-2012	LMDI
[51]	Du et al. (2018)	Journal of Cleaner Production	Energy-intensive industries	1986-2013	LMDI
[52]	Jia et al. (2018)	Journal of Cleaner Production	Industrial sector (Nanchang)	1998-2014	LMDI
[53]	Liu et al. (2018)	Journal of Cleaner Production	Cement sector	2005-2012	Spatial and temporal decomposition
[54]	Li et al. (2018)	Environmental Science and Pollution Research	Electricity sector	1990-2013	Decomposition analysis
[55]	Lin et al. (2018)	Energy	Industrial sector (Shanghai)	1960-2015	A dynamic vector autoregression analysis
[56]	Peng and Tao (2018)	Journal of Cleaner Production	Power sector	1980-2014	Three-dimensional decomposition
[57]	Wang et al. (2018)	Journal of Cleaner Production	Industrial sector	1999-2015	Spatial LMDI
[58]	Wang et al. (2018)	Energy Policy	Electricity sector	1995-2014	LMDI & Geographical effect
[59]	Wang et al. (2018)	Energy Economics	Industrial sector (Provincial level)	2006-2014	PDA & IDA & Attribution analysis
[60]	Wen et al. (2018)	Polish Journal of Environmental Studies	Electricity sector	2000-2014	STIRPAT
[61]	Yan et al. (2018)	Energies	Electricity sector	2000-2013	LMDI
[62]	Jiang et al. (2018)	Sustainability	Industrial sector	2000-2014	IDA
[63]	Zhao and Li (2018)	Energy & Environment	Industrial sector (Guangdong)	2000-2014	LMDI
[64]	Kang et al. (2014)	Energy	Multi-sector including industrial sector (Tianjin)	2001-2009	LMDI
[65]	Wang and Feng (2018)	Energy Economics	Industrial sector	2000-2015	LMDI

Table A4. Summary of indicators in studies on driving forces of CO_2 emissions.

ID	Drivers
[1]	Emissions coefficient; Energy intensity; Industrial activity; Energy structure; Industrial structure.
[2]	Energy mix; Energy intensity; Industrial structure; Industrial activity.
[3]	Industrial scale; Industrial structure effect; Carbon intensity (of output); R&D intensity; Energy efficiency; Energy structure.
[4]	Emission coefficient; Energy structure; Energy intensity; Steel production.

[5]	Energy mix; Energy intensity; Industrial structure; Industrial output
[6]	Output; Energy intensity; Energy mix; Emission coefficient
[7]	Emission coefficient; Energy structure; Energy intensity; Industrial structure; Industrial activity.
[8]	Industrial activity; Energy intensity; Energy mix; Emission coefficient.
[9]	GDP per capita; Population; Economic structure; Energy structure; Energy intensity.
[10]	Emissions coefficient; Energy structure; Energy intensity; Cement production activity; Clinker production activity.
[11]	The standard coal consumption rate for generating power; The average thermal power equipment utilization hour; the industrial added value of the power sector
[12]	Final energy consumption; Value added; Energy price; CO_2 emissions
[13]	Emission coefficient; Energy mix; Energy intensity; Industrial structure; Industrial activity.
[14]	Emission coefficient; Energy mix; Energy intensity; Industrial structure; Scale effect.
[15]	Industrial activity; Regional structure; Energy intensity; Energy mix; Emission coefficient.
[16]	Industrial activity; Industrial structure; Carbon intensity of output.
[17]	Emission coefficient; Energy intensity; Industrial structure.
[18]	Emission coefficient; Energy intensity; Energy structure; IVA per capita; The number of labors.
[19]	GDP growth rate; investment in fixed assets; internal expenditure on science and technology activities.
[20]	Population; GDP per capita; Industrial structure; Final demand structure; Production structure; Energy structure; Energy intensity.
[21]	Output per worker; Industrial scale; Energy intensity; Energy structure.
[22]	Emission coefficient; Energy structure; Energy intensity; Labor productivity (output per employee); Industry scale.
[23]	Economic scale; Industrial structure; Energy intensity; Energy structure; Emission coefficient.
[24]	Emission coefficient; Energy structure; Energy intensity; R&D efficiency; R&D intensity; Investment intensity; Industrial structure; Industrial scale.
[25]	Emission coefficient; Energy structure; Energy intensity; Industrial activity.
[26]	Industrial growth; Industrial structure; Energy structure; Energy intensity; Population.
[27]	GDP; Economic growth rate; Industrial structure; Population; Urbanization.
[28]	GDP; Economic growth rate; Industrial structure; Population; Urbanization; Road density.
[29]	GDP per capita; Energy efficiency; Urbanization; Industrialization; Energy structure.
[30]	Population; GDP per capita; Specific energy consumption; Urbanization; Industrialization; Energy structure.
[31]	GDP per capita; Urbanization; Industrialization; Energy structure; Energy efficiency.
[32]	GDP per capita; Urbanization; Industrialization; Energy structure; Energy efficiency.
[33]	Emission coefficient; Energy structure; Energy intensity; Industrial structure; Economic output.
[34]	Carbon coefficient; Energy mix; Energy intensity; Process carbon intensity; Investment efficiency; Investment share; Investment scale.
[35]	Industrial activity; Energy intensity, Energy structure.
[36]	Population; GDP per capita; Energy intensity; Urbanization; Industrialization; Energy structure (the proportion of coal consumption).
[37]	Emission coefficient; Fossil energy structure (the share of fossil fuels in total energy consumption); Regional thermal efficiency; Clean power generation (the share of thermal power generation in total electricity generation); The regional shift effect (the share of electricity in one region in national electricity).

[38]	Emission coefficient; Energy intensity; Industrial structure.
[39]	Energy Structure; Energy intensity; Economic output; Energy usage efficiency; Energy saving technology; GDP technical efficiency; GDP technology.
[40]	GDP per capita; Energy intensity; Urbanization.
[41]	GDP per capita; Energy efficiency; Urbanization; Industrialization; Energy structure.
[42]	Population; GDP per capita; Energy efficiency; Urbanization; Industrialization; Energy structure.
[43]	Population; GDP per capita; Energy efficiency; Urbanization level; Industrialization level; Energy structure.
[44]	Population; GDP per capita; Energy efficiency; Urbanization; Industrialization; Energy structure.
[45]	Industrial output; Industrial structure; Energy structure; Energy intensity; Structure of industrial enterprises (the number of state-owned enterprises, collectively-owned enterprises, private enterprises, and foreign invested enterprises); The proportions of the abovementioned four group enterprises
[46]	Population; GDP per capita; Coal consumption rate; Line lose rate; Power generation structure; Energy intensity; Industrial structure; Urbanization level.
[47]	Emission coefficient; Energy structure; Coal consumption rate; Power generation structure; The ratio of power generation to consumption; Power consumption scale; Production sectors' electricity intensity; Industrial structure; Household electricity intensity; Economic scale; Population size.
[48]	Energy structure; Energy intensity; Industrial structure.
[49]	Emission coefficient; Energy intensity; Process carbon intensity; Industrial structure; Industrial activity.
[50]	Emission coefficient; Energy structure; Energy intensity; Industrial structure; Industrial activity.
[51]	Industrial scale; Industrial structure; Energy intensity; Energy structure; Emission coefficient.
[52]	Population; Energy intensity; Industrial structure; Energy structure; GDP per capita.
[53]	(Energy-related CO_2 emissions) Effects of: Cement production; Clinker share to cement; energy intensity; Emission coefficient. (Process-based CO_2 emissions) effects of: emission factors of thermal decomposition of calcium carbonate; Emission factors of thermal decomposition of clinker production. (Indirect CO_2 from electricity) effects of: Cement production; Energy intensity; Emission coefficient.
[54]	Emission coefficient; Energy intensity; Share of electricity generation; Share of thermal power generation; Electricity intensity; Industrial activity; Population.
[55]	GDP per capita; Population; Energy efficiency (GDP per unit of energy); Urbanization; Industrialization; Energy structure.
[56]	Carbon emission coefficient; Thermal generation efficiency; Proportion of electricity generated from the fossil energy in total electricity production. (Intensity effect; Structure effect; Emission effect). The decomposition results of carbon intensity are represented as: technological innovation effect and structural adjustment effect.
[57]	Emission coefficient; Energy structure; Energy intensity
[58]	Geographic distribution effect (The share of provincial generation in domestic electricity production); Utilization efficiency effect (The ratio of energy input to electricity output in thermal electricity generation); Thermal power proportion effect (The proportion of thermal electricity generation in total domestic generation); Energy composition effect (The proportion of each type of fossil fuel in total fossil fuel consumption); Emission factor effect (The ratio of CO_2 emissions to energy consumption).
[59]	Energy mix effect; Potential regional output structure effect; Emission coefficient; Potential energy intensity; Output gap effect (the ratio of potential outputs to real outputs); Energy use technical efficiency effect; Energy use technological change effect; Desirable output technical efficiency effect; Desirable output technological change effect.

[60]	GDP per capita; Urbanization; Industrialization; Power-consuming efficiency on the demand side; Power generation efficiency on the production side; Electric power structure
[61]	Emission coefficient; Energy intensity; Industrial activity.
[62]	Carbon coefficient; Energy structure; Energy intensity; Industrial activity.
[63]	Emission coefficient; Energy structure; Energy intensity; Industrial activity.
[64]	Emission coefficient; Energy structure; Energy intensity; Structure; Industrial activity.
[65]	Emission coefficient; Energy structure; Energy intensity; R&D efficiency; R&D intensity; Investment intensity; and Industrial activity.

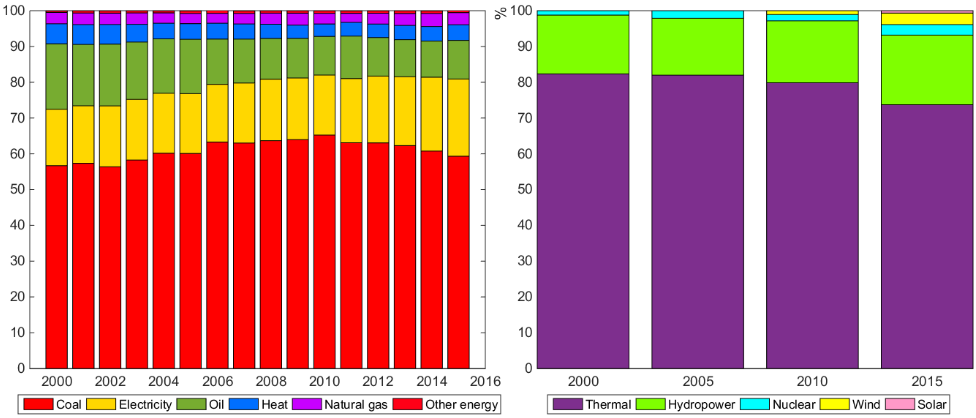

Fig. A1. The energy structure of China's industrial sector is shown in the left figure and the right one is the power generation structure. *Source*: China Energy Statistic Yearbook (2001-2016).

4. Detailed information on studies related to projections

The projections of CO_2 emissions in industrial sector and its major sub-sectors were analyzed in section 5.4 of the main body. 70 papers were selected. The authors, journals, study periods, methods, main outcomes and scenario assumptions were summarized in Tables A4-6.

Table A5. Detailed information of emissions projections studies.

ID	Author	Journal	Research object	Study period	Method
[66]	Kroeze et al. (2004)	Energy Policy	Electricity sector	1990-2020	RAINS-ASIA
[67]	Wang et al. (2007)	Energy Policy	Iron & steel sector	2000-2030	LEAP
[68]	Cai et al. (2007)	Energy Policy	Electricity sector	2000-2030	LEAP
[69]	Steenhof et al. (2007)	Energy Policy	Electricity sector	1980-2000	Kaya identity & Scenario analysis
[70]	Cai et al. (2008)	Energy Policy	Electricity, Iron & Steel, Cement	2000-2020	LEAP
[71]	Zhu et al. (2010)	Energy	Chemical sector	2000-2007	-
[72]	Akashi et al. (2011)	Energy	Industrial sector	2005-2030	Bottom-up model

[73]	Lei et al. (2011)	Atmospheric Environment	Cement sector	1990-2020	Technology-based method
[74]	Hara et al. (2011)	Sustainability Science	Industrial sector	2000-2020	LMDI & Vector Auto-regression (VAR) model
[75]	Chen et al. (2011)	Energy	Electricity sector	2011-2030	-
[76]	Ke et al. (2012)	Energy Policy	Cement sector	2011-2030	Analyses of historical production and physical and macroeconomic drivers
[77]	Hasanbeigi et al. (2013)	Energy	Iron & steel sector	2010-2030	Bottom-up Energy Conservation Supply Curves
[78]	Zhou et al. (2013)	Energy Policy	Industrial sector	2005-2095	Global Change Assessment Model (GCAM)
[79]	Tian et al. (2013)	Energy Policy	Iron & steel sector	2001-2030	LMDI & Scenario analysis
[80]	Chen et al. (2014)	Applied Energy	Iron & steel sector	2010-2050	System dynamics model& Bottom-up energy system model (TIMES)-(The integrated MARKAL-EFOM System)
[81]	Li & Zhu (2014)	Applied Energy	Iron & steel sector	2010-2030	Conservation supply curve
[82]	Lin & Long (2014)	Energy	Chemical process sector	1980-2020	Co-integration & Scenario analysis
[83]	Liu et al. (2014)	Applied Energy	Thermal Power sector	2003-2020	GM(1,1), Autoregressive integrated moving average model & Second order polynomial regression model
[84]	Wen and Li (2014)	International Journal of Greenhouse Gas Control	Non-ferrous metals sector	2010-2020	LEAP model, Technology-based model, Scenario analysis
[85]	Wen et al. (2014)	Journal of Cleaner Production	Iron & steel sector	2010-2020	Asian-Pacific Integrated Model (AIM)
[86]	Wen et al. (2014)	Energy & Environment	CO_2 mitigation of key sectors	2010-2030	Bottom-up combined with top-down models
[87]	Xu et al. (2014)	Applied Energy	Cement sector	1980-2050	Co-integration relationship
[88]	Lin and Ouyang (2014)	Energy	Non-metallic mineral products sector	1986-2020	LMDI & Scenario analysis

[89]	Wang et al. (2014)	Applied Energy	Electricity sector	2010-2030	Multi-region optimization model
[90]	Gao et al. (2015)	Frontiers of earth science	Steel sector	2010-2020	Identity & Scenario analysis
[91]	Wang et al. (2015)	Natural Hazards	Energy-intensive industries	2001-2015	Gray relational analysis & GM (1,1)
[92]	Wen et al. (2015)	Energy Policy	Cement sector	2010-2020	Asian-Pacific Integrated Model (AIM)
[93]	Yan and Fang (2015)	Journal of Cleaner Production	Manufacturing industry	1993-2020	LMDI & Scenario analysis
[94]	Gu et al. (2015)	Energy Procedia	Electricity sector	2000-2020	LMDI & Scenario analysis
[95]	Wen et al. (2015)	Greenhouse Gases-Science and Technology	Electricity sector	2009-2030	Bottom-up model
[96]	Li et al. (2015)	Energy Procedia	Cement sector	2010-2050	China TIMES model
[97]	Sun et al. (2016)	Energies	Electricity sector	1997-2020	STIRPAT
[98]	Wang et al. (2016)	Atmospheric Environment	Industrial sector	1996-2030	LMDI & Co-integration
[99]	Wang and Lin (2016)	Renewable and Sustainable Energy Reviews	Iron & steel sector	1985-2020	Co-integration & Scenario analysis
[100]	Wu and Peng (2016)	Energies	Electricity sector	2007-2030	LEAP model & Scenario analysis
[101]	Wu et al. (2016)	Applied Energy	Iron & steel sector	2013	Cost-effectiveness calculation model based on double benefits of energy saving and emission abatement
[102]	Yang and Lin (2016)	Renewable and Sustainable Energy Reviews	Electricity sector	1985-2020	LMDI & Scenario analysis
[103]	Yan et al. (2016)	Energy	Electricity sector	2000-2020	LMDI & Scenario analysis
[104]	Yuan (2016)	Energies	Electricity sector	2008-2020	Scenario analysis
[105]	Cui et al. (2016)	Environmental	Industrial sector	1991-2020	Kaya identity, LMDI

		Science and Pollution Research			method, Sector decomposition analysis
[106]	Xie et al. (2016)	Applied Energy	Petroleum refining and coking sector	1995-2039	LMDI & Scenario analysis
[107]	Xu et al. (2016)	International Journal of Greenhouse Gas Control	Cement sector	2011-2050	Bottom-up integrated assessment model
[108]	Zhang et al. (2016)	Discrete Dynamics in Nature and Society	Electricity sector	1990-2030	LMDI & Scenario analysis
[109]	Chen and Han (2016)	Applied Economics letters	Industrial sector	2003-2050	A managerial disposability intensity analysis framework based on the directional distance function
[110]	Khanna et al. (2016)	Utilities Policy	Electricity sector	2015-2050	Bottom-up energy modeling & scenario analysis
[111]	Yao et al. (2016)	Journal of Cleaner Production	Industrial sector	1995-2020	Environmental learning curve (ELC) model
[112]	Zheng et al. (2016)	Journal of Cleaner Production	Industrial sector (Jiangsu, Zhejiang, Shanghai)	2005-2030	Air pollution Interactions and Synergies (GAINS) model
[113]	Lin and Tan (2017)	Renewable and Sustainable Energy Reviews	Energy-intensive industries	1985-2030	LMDI & Co-integration
[114]	Liu et al. (2017)	Applied Energy	Cement sector	2001-2030	Scenario analysis & Technology diffusion curves
[115]	Meng et al. (2017)	Journal of Cleaner Production	Electricity sector	2001-2030	Scenario analysis
[116]	Wei et al. (2017)	Polish Journal of Environmental Studies	Iron & Steel Sector	2015-2040	LEAP model.
[117]	Xuan and Yue	Resources,	Steel sector	2014-2030	Scenario analysis &

	(2017)	Conservation and Recycling			Subsystem input-output model
[118]	Zhang et al. (2017)	Global Environmental Change	Industrial sector	1993-2035	LMDI, Dynamic Monte Carlo simulation & Scenario analysis
[119]	Zhao et al. (2017)	Polish Journal of Environmental Studies	Industrial sector	2017	Input-output model
[120]	Zhao et al. (2017)	Natural Hazards	Electricity sector	1985-2030	LMDI & Scenario analysis
[121]	Gao et al. (2017)	Renewable and Sustainable Energy Reviews	Cement sector	1980-2020	CO_2 emissions accounting (Process, fuel and electricity)
[122]	Li et al. (2017)	Applied Energy	Heavy chemical sector	1990-2015	ATIRPAT & CGE models
[123]	Ge et al. (2017)	International Journal of Sustainable Energy	Industrial sector (Tianjin)	2003-2022	GM (1,1) & LMDI & STIRPAT model
[124]	Li and Patino-Echeverri (2017)	Energy Policy	Electricity sector	2020	Bottom-up energy modeling & scenario analysis
[125]	Li et al. (2017)	Applied Energy	Cement sector	2010-2050	Combining the Stock-based model and the Integrated MARKAL–EFOM System model of China (China TIMES)
[126]	Zhu et al. (2017)	Journal of Cleaner Production	Industrial sector (Yangtze River Delta region)	2005-2020	LMDI & Scenario analysis
[127]	An et al. (2018)	Applied Energy	Iron & Steel Sector	2015-2030	National Energy Technology model
[128]	Li et al. (2018)	Journal of Cleaner Production	Non-ferrous metals sector	2010-2030	Bottom-up decomposition method
[129]	Wei et al. (2018)	Mitigation and Adaptation Strategies for Global Change	Cement sector	2001--2030	-
[130]	Zhang et al. (2018)	Applied Energy	Iron & steel sector	2015-2050	Dynamic MFA & Decomposition analysis
[131]	Zhou et al. (2018)	Energy	Industrial sector	2050	A modified global change

		Strategy Reviews			assessment model.
[132]	Zhao et al. (2018)	Ecological Indicators	Electricity sector	2010-2050	CGE (Computable general equilibrium) model
[133]	Zhang et al. (2012)	Computers & Chemical Engineering	Electricity sector	2010-2050	Optimization framework
[134]	Tang et al. (2017)	Applied Energy	Electricity sector	2016-2030	Power generation planning model
[135]	Zhang et al. (2017)	Energy	Electricity sector	2015-2030	Power system planning model

Table A6. Major results of emissions projections.

ID	Outcome
[66]	End use efficiency improvement is one of the most effective ways to reduce emissions, as well as the fuel switches. The end use energy efficiency could lead to 43% potential of emissions reduction, followed by the replacement of coal by renewable energy (23%) and natural gas (11%). Reduction in electricity losses during the transmission and distribution would also reduce emissions by 7% and the electrical efficiency improvement of power plants would result in 9% reduction.
[67]	There is great potential for emissions reduction of the iron and steel sector by adjusting the industrial structure and technology progress. The current sustainable policies could reduce the cost of emissions abatement.
[68]	Demand side management and circulating fluidized bed combustion are the first two choices for emissions reduction, followed by supercritical plants and the renovation of conventional thermal power plants. In the long run, nuclear and hydropower will play the dominant role in contributing to emissions reduction.
[69]	Improvements in generation efficiency has been the most important factor affecting the change in carbon intensity. Fossil fuel increased carbon intensity from 1980 to 2002; Auxiliary effect contributed to the decrease in carbon intensity from 1999.
[70]	China's policies since 2000 should be recognized and encouraged, if further emissions reduction was required. The policy-makers should take the sub-sector into consideration and make policies within or across sectors.
[71]	The technology improvement is not enough for the achievement of 40-45% reduction targets in carbon intensity.
[72]	The industrial production change has a strong effect on CO_2 emissions in the future. The currently available technologies could result in a large amount of emissions reduction.
[73]	The deployment of advanced energy-related technologies would lead to about 12.8% reduction in CO_2 emissions of the cement sector.
[74]	The diffusion of highly efficient technologies and the promotion of circular economy can potentially lead to energy savings and reductions in resource consumption associated with industrial activities.
[75]	The encouragement of low-carbon technologies in power generation is an effective way to reduce emissions.
[76]	The improvement in energy efficiency is an important way to reduce the energy and emissions intensities of the cement industry. However, policies to reduce total cement production is the most direct way for reducing total energy consumption and CO_2 emissions.
[77]	The cost-effective electricity saving would reduce the emissions by 1191 $MtCO_2$/yr during 2010-2030,

	while the technical fuel saving would cause a emissions reduction of 1205 $MtCO_2$/yr.
[78]	Industrial sub-sectors can play an important role in technological mitigation of GHG and the industrial sector could reach its emissions peak in 2035 with 9.3 $GtCO_2$/yr.
[79]	The production scale is responsible for the rapid increase in emissions; emission coefficient and energy intensity are two main factors contributing to the emissions reduction; Manufacture of General Purpose and Special Purpose Machinery and Manufacture of Transport Equipment could reduce their embodied emissions by 17% and 2%, respectively.
[80]	In the near future, the improvements in energy efficiency is the most effective way to reduce the energy and carbon intensities. However, the structure change in iron and steel production will be of great significance in the long run.
[81]	41 technologies would result in a CO_2 abatement contribution of 443.21 kg/t. Some promoted technologies are not cost-effective currently.
[82]	There is great potential for emissions reduction in the chemicals sector. The energy price could well affect the emissions reduction, so the market mechanism of energy price is of great importance.
[83]	Shanghai, Jiangsu, Zhejiang, Shandong and Fujian are thermal power generation concentrated areas with arduous task of carbon emissions reduction by 2020.
[84]	Aluminum could result in the most CO_2 emissions reduction. The policies should be provided for targeted metals, including aluminum, magnesium, zinc and copper.
[85]	The emissions reduction accounted for 14.5% of total emissions. The promotion of advanced technology is the most effective way for the ferrous metals sector to reduce CO_2 emissions.
[86]	The iron & steel industry will reach its emissions peak of 1.2~1.3 $GtCO_2$-eq during 2015-2020. The emissions peak of cement industry will be reached during 2015-2020 with 1.26~1.33 $GtCO_2$-eq. The direct CO_2 emissions in the aluminum industry will peak during 2015-2020 at 40~53 $MtCO_2$-eq.The electricity industry will reach its emissions peak during 2015-2020 with 4.4 -4.7 $GtCO_2$-eq. The emissions of oil industry will keep increasing before 2030.
[87]	It is possible to achieve the target of reducing 50% of CO_2 emissions in 2050 by continuous technology improvement and cement output reduction in China's cement industry. The contribution of clinker substitution is the greatest, followed by CCS technology. Cement output reduction is the major driver for CO_2 emissions reduction by 2050, and it contributes to 52% of total emissions reduction in the low demand case and 34% in the high demand case.
[88]	The industrial activity is the leading force for emissions increase while the energy intensity is the major contributor to the emissions mitigation. Effects of industrial scale and carbon intensity of energy show varying trends. The substitution effect has a small negative impact on the increase of CO_2 emissions.
[89]	If there is no additional carbon intensity policies, the total CO_2 emissions of electricity sector will increase to approximately 9.6 $GtCO_2$/yr in 2030. However, with the emissions targets, the CO_2 emissions would peak around 2025 and remain at about 7.1 $GtCO_2$/yr.
[90]	The growths of GDP and steel production are closely related to the 40-45% reduction targets of emissions. If their growth rates are lower than 3%, and the intensity reduction targets can be achieved.
[91]	The impacts of energy mix, energy intensity and industrial output on emissions of the six energy-intensive industries are significant; The forecast CO_2 emissions of petroleum, chemicals, non-metallic products, ferrous metals, nonferrous metals and electricity sectors are 385 $MtCO_2$/yr, 948 $MtCO_2$/yr, 1162 $MtCO_2$/yr, 2426 $MtCO_2$/yr, 482 $MtCO_2$/yr and 378 $MtCO_2$/yr in 2020.
[92]	With structural adjustment and improvement in the popularizing rate, the CO_2 emissions will be reduced by 270 $MtCO_2$/yr and 360 $MtCO_2$/yr in 2020 for the cement sector .
[93]	The economic scale was the major factor for emissions increase, and the energy intensity was the most important factor to decrease emissions. Future CO_2 emissions mitigation will mainly depend on the drops in energy intensity, declines in emission coefficient of electricity and upgrades in economic structure. Their additive effects will be 5412 $MtCO_2$/yr in 2020. However, the energy substitution with electricity is

not beneficial. It is necessary to combine different approaches to reduce the emissions. Thus, the emissions targets for 12th FYP can be achieved.

[94] The share of low-carbon generation and the improvement in efficiency of thermal power generation are the most important factor for future emissions reduction.

[95] The hydropower bears the highest total cost, while the cogeneration of heat and power bears the lowest cost. The technology with the highest total social benefit is also hydroelectricity, while the carbon capture and sequestration (CCS) yields the lowest social benefit. The top three technologies based on internal levelized cost are: the cogeneration of heat and power, biomass power generation, and wind power generation. Based on social levelized cost, the highest priority technologies are: the integrated gasification combined cycle, biomass power generation, and wind power generation.

[96] The carbon tax doesn't work significantly on the technology choice and CO_2 emissions reduction in the short term. However, in a long run, high carbon tax may increase the application of production with CCS or wasted heat recovery and cut down the small- and medium-sized plants.

[97] There are two important measures to reduce CO_2 emissions are the economic activity and low-carbon electricity technologies.

[98] Even though in the business-as-usual, the targets for carbon intensity in 2020 and 2030 can be achieved. However, the emissions peak of industrial sector would not can be reached until 2030 even though with lower energy intensity, lower economic growth and higher energy price.

[99] There is great reduction potential for emissions if there were higher share of renreables, labor productivity, technology and enrgy price.

[100] The emissions of electricity sector will range from 4074.16 $MtCO_2$/yr to 4692.52 $MtCO_2$/yr in 2020, and the emissions will be 3948.43- 5812.28 $MtCO_2$/yr in 2030. The targets of carbon intensity in electricity sector in both scenarios cannot be achieved both in 2020 and 2030.

[101] The improvement in 24 technologies could result in 291 $MtCO_2$/yr emissions reduction of the iron and steel industry.

[102] The electricity intensity and economic activity are primary drivers for the increase in CO_2 emissions, while the energy efficiency contributed to the emissions decrease and will play a key role in the future. With these drivers improvement, the emissions of electricity sector can be reduced by 2236 $MtCO_2$/yr in 2020.

[103] GDP per capita was responsible for the increase in CO_2 emissions, accounting for 120.36%. Followed by population, which accounted for 7.56%. The energy intensity was the primary factor to decrease CO_2 emissions (-22.93%). Energy structure also led to the decrease in CO_2 emissions (-5.07%) in most years. Emission coefficient had marginal effect on CO_2 emissions during the whole study period.

[104] The improvement of coal power operations, structures, technologies and the deployment of energy conservation could help the electricity sector to reduce the energy consumption and CO_2 emissions. The reduction potentials of different measures can result in the following emissions reduction in 2020: Operation improvement (-62.07 $MtCO_2$/yr); Coal power (-36.56 $MtCO_2$/yr); Clean energy (-304.55 $MtCO_2$/yr); Deployment of demand side management (-186.46 $MtCO_2$/yr); The total emissions reduction is 589.64 $MtCO_2$/yr.

[105] The economic output was the leading force of emissions increase in each sector while the energy intensity and sector contribution were major contributors to the emissions mitigation. CO_2 intensity had no significant influence on CO_2 emissions in the short term. The energy mix had a small but growing impact on emissions decline.

[106] The industrial activity and energy intensity are the key factors that contribute to the increase and decrease in emissions of the petroleum sector, respectively. If the energy-saving technology could be improved and the energy mix could be adjusted, 306 $MtCO_2$/yr emissions will be reduced which accounts for almost 30% of the emissions in business-as-usual in 2030.

[107] The waste heat recovery and clinker substitution are two cost-effective ways for emissions reduction in the cement sector over the planning horizon (2011-2050). The improvement in energy efficiency and

	alternative fuels are key factors for achieving the mid-term emissions target around 2030. The technology lock-in effect is an important factor that limits the diffusion of energy efficiency improvement technology after 2030. CCS technology is necessary for the cement industry to achieve stringent emissions reduction targets.
[108]	The industrial scale and energy intensity are the major driving factors for CO_2 emissions in electricity sector. With the improvements in energy structure, energy intensity, capital efficiency and industrial scale, the emissions of electricity sector can be reduced by 491 $MtCO_2$/yr and 2734 $MtCO_2$/yr in 2020 and 2030, respectively.
[109]	When the industrial growth rate is 6% and the energy consumption growth rate is 2.8%, the contradiction between environment and industrial development is least. In this way, the numbers of industrial sectors that can achieve win–win development are the most, which will help China to achieve the emissions peak in 2030.
[110]	The green dispatch could cause the CO_2 emissions of power sector to peak with 5.37 $GtCO_2$/yr in 2038 instead of 5.83 $GtCO_2$/yr in 2040 based on the continuation of equal shares dispatch. If more aggressive renewable policies were adopted in addition to the green dispatch, the CO_2 emissions of power-sector could peak in 2030, with additional reductions of 2.61 $GtCO_2$/yr annually in 2050. Install the base CCS capacity will allow the of CO_2 emissions power sector to peak two years earlier with 5.3 $GtCO_2$/yr in 2036, while doubling the CCS capacity will further lower the peak CO_2 emissions by 50 $MtCO_2$/yr but will not change the peak year. Accelerated coal-generation efficiency will achieve relatively small annual CO_2 emissions reductions, with 28-55 $MtCO_2$/yr, but can shift CO_2 emissions peak of power sector two years earlier (to 2037).
[111]	Manufacture of Foods has the largest reduction potential (60.8% in BAU and 65.3% in planned scenario). The reduction potential of six energy-intensive industries, petroleum, chemicals, non-metallic products, ferrous metals, non-ferrous metals and electricity sector is 8.8%, 16.8%, 41.3%, 24.6%, 37.3% and 48.6%, respectively in BAU scenario, while the potential will be 18.4%, 28.9%, 47.6%, 34.8%, 47% and 52.5%, respectively in planned scenario.
[112]	696.92, 572.38 and 262.22 $MtCO_2$/yr in 2030 for Jiangsu, Zhejiang and Shanghai respectively with the growth rate ranging from 61.1% (Jiangsu), 89.7% (Shanghai) to 92.2% (Zhejiang);
[113]	The decrease in energy intensity is the main contributor to emissions decrease. Increase in labor productivity and industrial scale causes sharp increase in CO_2 emissions. There is great potential for emissions reduction of energy-intensive industries in the future.
[114]	The command-and-control approach for energy saving in China's cement sector are effective. The carbon price can speed up the diffusion of certain technologies and lead to emissions reduction to a certain degree.
[115]	The China's electricity sector cannot easily reach its CO_2 emissions peak before 2030. The increase in total electricity consumption is the most important contributor to the CO_2 emissions growth.
[116]	The effects of four scenarios on emissions reduction are ranked as follows: emissions trade scenario > cut excessive capacity scenario > technology improvement scenario > business-as-usual scenario.
[117]	The structure adjustment, developing a circular economy and a shift from the iron ore-based to scrap-based steel production is important for emissions reduction in China's ferrous metals sector.
[118]	Even in the business-as-usual, the 2020 and 2030 intensity-reduction targets can be achieved. With the strong efficiency improvement and structural adjustment, the industrial CO_2 emissions will peak in 2025. With high/low efficiency improvement and weak structural adjustment, the industrial emissions cannot reach the peak before 2035.
[119]	The final demands keep the dominant role in pushing sectoral emissions increase. The technical progress leads to the emissions decline. Special energy-saving technical progress will gradually exceed universal technical progress in reduction effects. The high emission sectors are the best selection to gain favorable incentive policies to promote the emissions reduction. With incentive policies being improved, technical progress reduction effect is increasing. However, it is not enough to offset the driving effect from final demands growing in seven scenarios. More favorable incentives and investments should be allocated into

	high emission sectors, especially into the most sensitive ones.
[120]	The industrial scale is the major contributor to CO_2 emissions growth, while energy intensity is the main factor for CO_2 emissions decline. There is great potential for emissions reduction with the lower energy intensity and less industrial output.
[121]	Even with the best production scenario, it will be very challenging for China's cement industry to achieve the carbon intensity reduction of 40-45% by 2020.
[122]	The carbon emission peak would not be achieved under baseline scenario. The reduction policies have a moderate impact on increasing output and GDP but a substantial impact on decreasing energy consumption and carbon emission.
[123]	The economy scale was the most important factor driving the increase in CO_2 emission, followed by the economic structure and energy consumption. The energy structure had little effect on carbon emissions. The energy intensity played a certain role in inhibiting carbon emissions;
[124]	Comparing the results obtained under different scenarios, the development of renewables and the mandate for retrofits of existing coal-fired power plants are the most important ways to reduce the energy consumption and emissions of electricity sector.
[125]	Through the adoption of three alternative abatement measures, such as the fuel switch, implementing the energy-efficient measures and CCS, China's cement sector could potentially achieve a great reduction in CO_2 emissions.
[126]	The economic output is the greatest contributor for the emissions increase, followed by population. The energy intensity and energy structure are the two main emissions mitigation factors. The driving factors of CO_2 emissions in the cities exhibit distinct spatial characteristics, indicating that future analyses of cities should be a research focus. With the improvements of the drivers, the reduction potential of CO_2 emissions is significant.
[127]	The most effective way to reduce CO_2 emissions of the ferrous metals sector is promoting low-carbon technologies along with cost minimization, which could lead to a cumulative reduction of 818.3 $MtCO_2$/yr from 2015 to 2030 compared with the existing policies and measures.
[128]	In the high production scenario, the total CO_2 emissions is 321 $MtCO_2$/yr in 2030 which increase by 137% from 2015. In the low production scenario, the CO_2 emissions will peak in 2025 with 296 $MtCO_2$/yr. The energy efficiency policies show that the improvement of the energy efficiency are moderate. The CO_2 emissions of the non-ferrous metals sector is very likely to peak before 2030 with current policies.
[129]	CO_2 intensity of China's cement sector could be reduced by 55–58% and 59-69% in 2020 and 2030, respectively, indicating that China's cement industry can fully achieve the international commitments.
[130]	The energy consumption and CO_2 emissions will gradually decline under the synergistic effect of the technology promotion and structure adjustment. In the short term, they will depend more on technology improvement. In the long term, particularly after 2040, promotion of the production structure adjustment will be the main driver.
[131]	The energy consumption and CO_2 emissions growth will peak by 2025 and decrease up to 2050. In the reference scenario, the peak of energy consumption and CO_2 emission will be 2.42 Gtce/yr and 4.43 $GtCO_2$/yr, respectively. In the low-carbon scenario, the peak value will be 2.28 Gtce/yr and 4.13 $GtCO_2$/yr, respectively.
[132]	Compared with the carbon emissions trading, the carbon tax plays a more active role in reducing CO_2 emissions. The participation of all sectors in the carbon market result in more emissions right demand than partial participation of some sectors, and the whole power sector tend to reduce more CO_2 emissions and gain more economic benefits. Compared with the auction form of the permit allocation, mitigation costs of the power enterprises in the free permit allocation mechanism increase directly, which narrows the emission-reduction potential of the power sector.
[133]	The increase of carbon price, the shares of nuclear and renewables (mainly wind and solar PV power) in China's total power generation will increase quickly. However, in view of the higher cost of low-carbon

	technologies, fossil fuel power will keep a large total capacity over 2010-2050.
[134]	From 2016 to 2030, the fuel costs and the operation and maintenance costs will decrease obviously. The total carbon emissions from coal-fired power industry can significantly be reduced.
[135]	If the generation expansion planning and transmission expansion planning worked separately, the CO_2 emissions of electricity sector in 2030 will be 7.12 $GtCO_2$/yr. If the generation expansion planning and transmission expansion planning worked together, the emissions will be 6.86 $GtCO_2$/yr in 2030. If the integrated source-grid-load planning was carried out, the emissions of the electricity sector will be 6.61 $GtCO_2$/yr.

Table A7. Scenario assumptions of previous studies.

ID	Scenarios	Scenario assumptions
[66]	BAU	BAU (Business-as-usual): energy scenario based on short-term policies.
	BPT (Best practice technology)1	Mixed options: 70% improvement of energy use efficiency; Replacement of coal by renewables (without increase in hydro power); 100% Efficiency improvement in power plants; 100% reduction of loses during transmission and distribution.
	BPT 2	Efficiency improvement: 100% improvement of energy use efficiency; 100% efficiency improvement in power plants; 100% reduction of loses during transmission and distribution.
	BPT 3	Fuel switch: 40% improvement of energy use efficiency; 100% replacement of coal by renewables; 100% replacement of coal by natural gas; 100% replacement of coal by nuclear power.
	BPT 4	Theoretical maximum: 100% improvement of energy use efficiency; 100% replacement of coal by renewables; Natural gas is used to replace coal that is not avoided by other options; 100% efficiency improvement in power plants; 100% reduction of loses during transmission and distribution.
[67]	Baseline	Only take into account the industry policies adopted before 2000. Some backward technologies and equipment are identified, along with the need to eliminate them, such as mold casting, open hearth furnaces, small blast furnaces, and small electric furnaces etc. But a strong demand for steel products restricts the shift in industry structure and technological improvement. A large proportion of the output is still from small and medium plants. The overall technical level is lower than current policy. Certain energy-saving measures are adopted and energy intensity continues declining slowly.
	Current policy	Take into account policies adopted between 2000 and 2005. Industrial concentration increases, and larger modern steel enterprise groups gradually dominate the market. The production capacity of larger enterprises expands further, and technical equipment also improves. Small equipment is quickly eliminated. More energy conservation technologies are applied. There is a large increase in dry coke quenching and other exhaust gas and heat recovery equipment.
	New policy	Industrial concentration is stronger than current policy scenario. The proportion of super large equipment is higher. Exhaust gas and heat recovery devices are almost all-pervading. Structure adjustment for production processes is stronger. Through increased waste steel recycling, the proportion of electric arc furnaces and other modern technologies is greater.
[68]	Baseline	It remains the historical tendency until year 2020.
	Current policy	Planning and policies until 2005 have been emphasized. Advanced generation technologies have been widely introduced. Renewable energy will be

		encouraged.
	New policy	Pressure from achieving energy conservation and emissions reduction has prompted the implementation of stricter policies and sectoral regulation. Small-capacity power plants will be eliminated. Supercritical turbine generators will be used in projects from 2015. Carbon capture and storage (CCS) starts service in 2020. Other advanced coal-fired technologies will be used to a larger extent. Clean energy power plants will have a bigger generation ratio.
[69]	BAU	This scenario is based upon known economic and energy plans in China, including information available on the 10th and 11th national 5-year plans.
	Conservative scenario	It assumes the economic growth rate is 6.5% per annum until 2010, and decreases to 6% between 2010 and 2020.
	Optimum	Economic development is broad based, initiatives to ‘develop the west’ and increase rural incomes are successful. A strong, broad based domestic savings rate enables continued high rates of fixed capital investment. Most industrial sectors are led successfully along a model of socialistic market capitalism. Manufacturing, high tech and service based sub-sectors experience strong growth. Strong integration and trade with the outside world.
[70]	Pre-2000 Policy	Implementation of policies and projects announced prior to 2000. The energy efficiency improvement is at different degrees. Fuel price index, exchange rate and discount rate are the same in these three scenarios.
	Recent Policy	Implementation of policies announced before 2006. The energy efficiency improvement is at a higher degree than Pre-2000 Policy Scenario.
	Advanced Options	Implementation of select packages of GHG mitigation options. The energy efficiency improvement is at a higher degree than Recent Policy Scenario.
[71]	Baseline	Technologies are similar to 2007; the outputs will continue to grow at an annual rate of 2%.
	Low technological improvement rate	Technologies will improve to a small extent.
	High technological improvement rate	Technological improvements can reach significant widespread achievements.
[72]	Frozen scenario	It assumes the diffusion rate and energy efficiency of the technologies are fixed at the same level as in 2005.
	Scenario 1	It assumes the introduction of emissions reduction technologies is under \$20/tCO_2.
	Scenario 2	It assumes the introduction of emissions reduction technologies is under \$50/tCO_2.
	Scenario 3	It assumes the introduction of emissions reduction technologies is under \$100/tCO_2.
[73]	High scenario	The key technological features of the cement industry are projected based on the existing policies on the industry structure, energy saving and emissions control, but with high cement production.
	Medium scenario	Assumption of medium cement production.
	Low scenario	Assumption of low cement production.
[74]	BAU	The BAU scenario uses current trends as a basis for GDP growth forecasts, population growth, and elasticity (percentage change in energy consumption to

		achieve a 1% change in national GDP). The production of materials such as cement and steel are assumed to proceed at the current pace, and only nominal changes are assumed for technology innovations in the industrial sector.
	Diffusion of best-available technologies	Promotion of technology diffusion and a circular economy in industrial sectors.
[75]	Reference scenario (REF)	The super-critical and ultra-super-critical technologies are always available. The integrated gasification combined cycle and carbon capture and storage technologies are unavailable. The carbon price is set as 11.7 /tCO_2, which could be resulted from carbon trading mechanism or carbon tax. No compulsive reduction targets are set by the government.
	Improved dispatching (IMD)	The IMD scenario is defined by changing to the improved dispatching model.
	Rapid wind (RAW)	The RAW scenario is defined with promotion in targets of wind.
	Rapid nuclear (RAN)	The RAN scenario is defined with promotion in targets of nuclear.
	Mature integrated gasification combined cycle (MIG)	In MIG scenario, the integrated gasification combined cycle is available after 2015.
	Non-CCS (NCS)	In NCS scenario, the improved dispatching mode is adopted. IGCC is available after 2015 and planning targets for wind as well as nuclear are both promoted.
	Mature CCS normal (MCS-N)	In MCS-N scenario, CCS will be available after 2020.
	Mature CCS early (MCS-E)	In MCS-E scenario, the learning effect was enhanced by 20% to advance the available year to 2015
	Mature CCS normal with double price for CO_2 allowance (MCS-D)	In MCS-D scenario, settings on CCS are the same as MCS-N and price for CO_2 allowance would be doubled.
	Slight compulsive emission reduction targets (CRT-S)	20% of reduction rate in 2030 are respectively set in CRT-S scenario with the emission level in 2010 as baseline.
	Large compulsive emission reduction targets (CRT-L)	40% of reduction rate in 2030 are respectively set in CRT-L scenario with the emission level in 2010 as baseline.
	The most optimistic scenario(OPM)	The OPM scenario is defined in which all the favorable conditions for carbon abatement are incorporated, including improvements in dispatch mode, rapid developments in wind, nuclear, IGCC and CCS, double carbon price and 40% compulsive emission reduction targets.
[76]	BIC (Building and Infrastructure Construction-based) Frozen scenario	The frozen scenario is constructed based on 2009 production and energy data of China's cement sector and reflects a future path at the current energy efficiency and emission level without further efficiency improvement. The cement output projections are based on the Lawrence Berkeley National Laboratory's China building and infrastructure construction forecast. The same assumption is followed by BIC Reference scenario, BIC Efficiency scenario and BIC Best practice scenario.
	BIC Reference scenario	Take into account current production trends and assume different implementation levels of efficiency measures, technologies and fuel switching policy choices.
	BIC Efficiency	Faster efficiency improvement than reference scenario

	scenario	
	BIC Best practice scenario	The best practice scenario assums that the cement production instantly reaches the current world best practice energy intensity and implements currently available aggressive energy efficiency and carbon reduction measures by 2011 and stays at that level from then on. Alternative fuels would replace coal as the main fuels and coal share would be reduced to 40%. The penetration of waste heat recovery power generation would be 100% and average of 36 kWh of electricity can be produced per t clinker.
	PCPC (Peak Consumption Per Capita-based) Frozen scenario	The frozen scenario is constructed based on 2009 production and energy data of China's cement industry and reflects a future path at the current energy efficiency and emission level of China's cement sector without further efficiency improvement. The annual cement consumption per capita will increase to 1544 kg by 2015, and then decrease to 1366 kg by 2020, 1000 kg by 2030. The PCPC Reference, Efficiency and Best practice scenario will follow this output assumption.
	PCPC Reference scenario	Take into account current production trends and assuming different implementation levels of efficiency measures, technologies, fuel switching policy choices.
	PCPC Efficiency scenario	Faster efficiency improvement than reference scenario
	PCPC Best practice scenario	The best practice scenario assums that the cement production instantly reaches the current world best practice energy intensity and implements currently available aggressive energy efficiency and carbon reduction measures by 2011 and stays at that level from then on. Alternative fuels would replace coal as the main fuels and coal share would be reduced to 40%. The penetration of waste heat recovery power generation would be 100% and average of 36 kWh of electricity can be produced per t clinker.
	FAI (Fixed Assets Investment-based) Frozen scenario	The frozen scenario is constructed based on 2009 production and energy data of China's cement industry and reflects a future path at the current energy efficiency and emission level of China's cement industry without further efficiency improvement. The annual cement consumption per capita during 2011-2015 is 1594 kg. Then the annual cement consumption will be 750 kg/yr until 2030. The cement outputs of FAI Reference, Efficiency and Best practice scenarios will follow this assumption.
	FAI Reference scenario	Take into account current production trends and assuming different implementation levels of efficiency measures, technologies, fuel switching policy choices.
	FAI Efficiency scenario	Faster efficiency improvement than reference scenario
	FAI Best practice scenario	The best practice scenario assums that the cement production instantly reaches the current world best practice energy intensity and implements currently available aggressive energy efficiency and carbon reduction measures by 2011 and stays at that level from then on. Alternative fuels would replace coal as the main fuels and coal share would be reduced to 40%. The penetration of waste heat recovery power generation would be 100% and average of 36 kWh of electricity can be produced per t clinker.
[77]	Technology 1	Injection of natural gas in blast furnace
	Technology 2	Injection of pulverized coal in blast furnace to 130 kg/t hot metal
	Technology 3	Preventative maintenance in integrated steel mills

	Technology 4	Preventative maintenance in electric arc furnace plants
	Technology 5	Energy monitoring and management systems in integrated steel mills
	Technology 6	Energy monitoring and management systems in electric arc furnace plants
	Technology 7	Recuperative and regenerative burner
	Technology 8	Heat recovery from sinter cooler
	Technology 9	Injection of coke oven gas in blast furnace
	Technology 10	Recovery of blast furnace gas
	Technology 11	Heat recovery on the annealing line
	Technology 12	Waste heat recovery from cooling water
	Technology 13	Recovery of basic oxygen furnace gas and sensible heat
	Technology 14	Coke dry quenching
	Technology 15	Coal moisture control
[78]	RES(Reference)_Low	All scenarios use the same social and macroeconomic drivers including population and labor productivity. The Reference scenario has no greenhouse gas emissions constraints or taxes. The low scenario follows the Western Europe pathway, which in 2050 reaches Western Europe's 2005 per-capita levels for both steel and cement (0.42 t of steel and 0.51 t of cement).
	RES_High	The high scenario converges to Japan's historical per-capita consumption, reaching 0.65 t of steel and 0.73 t of cement.
	RES_Middle	The middle scenario (RES_Middle) is the average of the above two scenarios.
	Low45	Scenario with carbon price, setting to limit radiative forcing not to exceed 4.5 W/m2. The steel and cement per capita follow the assumption of the low scenario.
	Middle45	Scenario with carbon price, setting to limit radiative forcing not to exceed 4.5 W/m2. The steel and cement per capita follow the middle scenario.
	High45	Scenario with carbon price, setting to limit radiative forcing not to exceed 4.5 W/m2. The steel and cement per capita follow the high scenario.
	Low26	Much higher carbon prices imposed, which is set to limit end-of-century radiative forcing to 2.6 W/m2. The steel and cement per capita follow the assumption of the low scenario.
	Middle26	Much higher carbon prices imposed, which is set to limit end-of-century radiative forcing to 2.6 W/m2. The steel and cement per capita follow the middle scenario.
	High26	Much higher carbon prices imposed, which is set to limit end-of-century radiative forcing to 2.6 W/m2. The steel and cement per capita follow the high scenario.
[79]	BAU	BAU scenario assums that nothing will be changed and the values of IPR (idle proportion of newly built residential buildings), DPR (demolition proportion of old residential buildings), DPN (demolition proportion of old non-residential buildings), RPM (remanufacturing proportion in Manufacture of General Purpose and Special Purpose Machinery sector) and RPE (recycling proportion of End-of-Life Vehicles) are 16%, 11%, 9%, 5% and 56%, respectively.
	High-efficiency	HE scenario is the best practice scenario in which mitigation actions and

	scenario (HE)	policies obtain maximum reduction on the demand of iron and steel products. IPR value is reduced to 4%. DPR value and DPN value decrease to 5% and 4.5%. RPM increase to 25%. RPE value increase to 90%.
	Median-efficiency scenario (ME)	ME scenario is moderate scenario.
	Low-efficiency scenario (LE)	LE scenario is another moderate scenario. ME scenario is better than LE scenario.
[80]	Baseline	The penetration rate of energy-saving technologies will reach 75% and 50% for key and non-key producers, respectively, in 2050. Pulverized coal injection will reach the currently advanced level of 180 kg/t. The share of pig iron in EAF (electric arc furnace) will decrease to 15% in 2050. The collection rate will increase to 50% in 2050.
	Low-Production scenario	The saturation level of products in each industry will be 10% lower than the baseline scenario, while the expected lifetime of buildings is 10% longer.
	High-Production scenario	Saturation level of products in each industry will be 10% higher than the baseline scenario, while the expected lifetime of buildings is 10% shorter.
	Low-Energy efficiency scenario	The penetration rate of energy saving technologies will reach 50% and 30% for key and non-key producers, respectively, in 2050. The pulverized coal injection will reach 150 kg/t.
	High-Energy efficiency scenario	The penetration rate of energy-saving technologies will reach 90% and 70% for key and non-key producers, respectively, in 2050. The pulverized coal injection will reach the international advanced level of 200 kg/t.
[81]	BAU	Share increase of cost-effective technologies is 10% in 2020 and 20% in 2030 compared with 2010. Share increase of non-cost-effective technologies is 10% in 2020 and 20% in 2030 compared with 2010.
	Cost-effective scenario	Share increase of cost-effective technologies is 20% in 2020 and 40% in 2030compared with 2010. Share increase of non-cost-effective technologies is 10% in 2020 and 20% in 2030 compared with 2010.
	Technical diffusion scenario	Share increase of cost-effective technologies is 20% in 2020 and 40% in 2030 compared with 2010. Share increase of non-cost-effective technologies is 20% in 2020 and 40% in 2030 compared with 2010.
[82]	Baseline	The explanatory variables will grow at the average annual growth rate over the years.
	Medium scenario	The scenario is the average of the BAU and the advanced scenario.
	Advanced	The explanatory variables increase in a way that can result in the largest emission reduction potential. The growth rates of variables are from 12th FYP, other studies and the indexes in developed countries (Japan).
[83]	BAU	The combination models are used to predict CO_2 emissions. There is no scenario assumption in this paper.
[84]	BAU	In this scenario, technologies employed in the sub-sectors are assumed to remain similar to those used in 2010, which also means that energy performance and CO_2 emissions per unit of production will remain the same throughout.
	Scenario 2: low technological improvement rate (LT)	Strict norms for energy consumption per unit of production are issued and an energy-efficiency target is set up to encourage enterprises adopt more advanced technologies. The policy of eliminating backward technology is also strengthened.

	Scenario 3: high technological improvement rate (HT)	Implementation of tough standards to eliminate backward equipment. It also promotes the use of advanced technologies. New policies include compulsory rules, market-based policies and voluntary measures.
[85]	BAU	No further energy saving and emissions reduction policy measures will be implemented during the scenario period. Industry technical structure, product structure and technology popularizing rate will maintain values in 2010, and only the scale of industry production changes.
	Integrated policy (INT) scenario	A series of policies and measures aimed at saving energy and reducing emissions were assumed to have been implemented. The industry technology structure and product structure have been adjusted. The technology popularizing rate is simulated based on the external policy environment of the AIM/end-use model. It takes into account compulsory measures, including elimination of backward production processes, setting energy and emissions constraints, and implementing economic incentives, mainly referring to cost subsidies for advanced technologies and carbon taxes. The carbon tax is set to 50 yuan/tons CO_2.
	The strengthen policy (STR) scenario	This scenario was built very similarly to the INT scenario, but with a higher intensity for policy implementation. For example, the carbon tax is increased to 100 yuan/tons CO_2 in the STR scenario.
[86]	SL (Social Low)-BAU	GDP and urbanization increase at a low speed. The baseline scenario ignores national commitments and pressure on CO_2 control, and continues with policies prior to 2010. Technology popularisation rate increases appropriately.
	SL-CW (Control Weak)	GDP and urbanization increase at a low speed. 2011-2015 industrial technology scenarios consider the “12th Five-Year Plan”, as it relates to various energy-saving measures and industrial development after 2010.
	SL-CM (Control Middle)	GDP and urbanization increase at a low speed. The economic structure is further optimised to increase energy savings and emission reduction efforts, including further input into the development of a low carbon economy and conservation practices in production and consumption. China’s 2020 commitments on emission reduction targets are used as an important reference.
	SL-CS (Control Super)	GDP and urbanization increase at a low speed. Based on voluntary emissions reductions, and taking into account global emissions reduction goals, China shifts to a low-carbon economy, developing and applying low-carbon technologies and strengthening international cooperation. Technology dissemination reaches the expected maximum in China.
	SH (Social High)-BAU	GDP and urbanization increase at a high speed. The growth rate of Population is the same as social low scenario. The baseline scenario ignores national commitments and pressure on CO_2 control, and continues with policies prior to 2010. Technology popularisation rate increases appropriately.
	SH-CW	GDP and urbanization increase at a high speed. The growth rate of Population is the same as social low scenario. 2011-2015 industrial technology scenarios consider the "12th Five-Year Plan”, as it relates to various energy-saving measures and industrial development after 2010.
	SH-CM	GDP and urbanization increase at a high speed. The growth rate of Population is the same as social low scenario. The economic structure is further optimised to increase energy savings and emission reduction efforts, including further input into the development of a low carbon economy and conservation practices in production and consumption. China’s 2020 commitments on emission reduction targets are used as an important reference.

	SH-CS	GDP and urbanization increase at a high speed. The growth rate of Population is the same as social low scenario. Based on voluntary emissions reductions, and taking into account global emission reduction goals, China shifts to a low-carbon economy, developing and applying low-carbon technologies and strengthening international cooperation. Technology dissemination reaches the expected maximum in China.
[87]	Scenario 0 (frozen efficiency scenario)	All parameters are set at their 2006 values and kept constant.
	Scenario 1 (efficiency improving scenario)	Thermal efficiency is fixed at the BAT (best available technology) level, while other factors are kept at their 2006 values.
	Scenario 2 (efficiency and alternative fuel scenario)	Thermal efficiency and the use of waste as alternative fuels are fixed at the BAT levels, while other factors are kept at their 2006 values.
	Scenario 3 (all factors improved excluding CCS scenario)	Thermal efficiency, the use of waste as alternative fuels and clinker substitution are fixed at the BAT levels, while CCS technology is kept at its 2006 values.
	Scenario 4 (BAT scenario)	All technology parameters are fixed at the BAT levels.
	Scenario 5 (Extreme scenario)	All technology parameters are fixed at their extreme values.
[88]	BAU	The parameters chosen for BAU are the average growth rate of each variable (emission coefficient, energy structure, energy intensity and industrial activity) during 1986-2010.
	Scenario 1	Higher emission scenario: growth rate of each factor is 2% higher than BAU.
	Scenario 2	Lower-emission scenario: growth rate of each factor is 2% lower than BAU.
[89]	NC scenario	No emission control policy.
	LC scenario	An emission control policy of local air pollution targets.
	OC scenario	Post-2020 CO_2 control targets only known to the sector during 2020-2030.
	AC scenario	Post-2020 CO_2 control targets known during 2010-2020.
	SQ scenario	Same as the OC scenario with LAP control targets.
	AD scenario	Same as the AC scenario with LAP control targets.
[90]	Scenario 1	According to the 12th Five-year Plan Scheme for China, the growth rates of GDP are respectively 7% and 4% during 2010-2015 and 2016-2020. Based on the industrialization experiences of the United States and Japan, the growth rate of steel output is 3% higher than the GDP growth rate.
	Scenario 2	The growth rates of GDP are the same as those in scenario 1. The growth rate of steel output is 7% higher than those of GDP.
	Scenario 3	The growth rate of GDP during 2000-2010 was the actual GDP growth rate in China from 2000 to 2010. The growth rates of GDP during 2010-2015 and 2016-2020 are the same as those in scenario 1. The growth rate of steel output from 2000 to 2020 was 3% higher than those of GDP.
	Scenario 4	The growth rate of GDP during 2000-2010 was the actual GDP growth rate in China from 2000 to 2010. The growth rates of GDP during 2010-2015 and 2016-2020 are the same as those in scenario 1. The growth rate of steel output from 2010 to 2020 was 7% higher than those of GDP.

[91]	BAU	-
[92]	BAU (S1)	No further energy saving and emissions reduction policies will be implemented between 2010 and 2020. And the industrial structure (technical structure and product structure), technology popularizing rate and external policy environment will maintain the level in 2010. Only the production scale of cement industry keeps the change. There is no external policy elements should be set additionally.
	Integrated policy scenario (S2)	Several measures will be implemented in order to simulate the potential for energy saving and emissions reduction by technology promotion, such as elimination of vertical kiln before 2015, elimination of small dry kiln and restricted technologies before 2020. In the economic incentive measures, six technologies will be the priority to get cost subsidies by 20%, while two technologies have the second priority to obtain cost subsidies by 15%. The amount of carbon tax will be set as 50 Yuan/t CO_2.
	The strengthen policy scenario (S3)	S3 scenario is very similar to S2 scenario but with a higher policy extent. For example, the elimination of outdated production capacity such as vertical kiln, small dry kiln and restricted technologies, will be completed before 2015. And the subsidies for cost will be increased to 20% of two technologies, and 25% of six technologies. The amount of carbon tax will be set as 100 Yuan/t CO_2.
[93]	S1 (Baseline)	The economic growth is 9% during 2012-2015 and 8% during 2016-2020. Emission coefficient, energy structure, energy intensity and industrial structure are the same as 2011.
	S2	Energy intensity in nine subsectors fall by 20%, 20%, 18%, 20%, 20%, 18%, 18%, 22% and 18%, respectively, compared with 2010. Other parameters, including emission coefficient, energy structure, industrial structure and economic growth are the same as Scenario 1.
	S3	The share of high-tech industries increase by 3%, and the share of energy-intensive industries decrease by 3%. Other parameters, including emission coefficient, energy structure, energy intensity and economic growth are the same as Scenario 1.
	S4	The emission coefficient of electricity falls at an average annual rate of 4.21% during 2012-2015 and 0.88% during 2016-2020. Other parameters, including energy structure, industrial structure, energy intensity and economic growth are the same as Scenario 1.
	S5	In 2015, the shares of coal, petroleum product, natural gas, heat and electricity will be 36.25%, 15.86%, 7.37%, 4.89% and 35.63%. In 2020, the shares of coal, petroleum product, natural gas, heat and electricity will be 27.63%, 14.76%, 9.87%, 4.89% and 42.86%. Other parameters, including emission coefficient, energy intensity, industrial structure and economic growth are the same as Scenario 1.
[94]	BAU	China does not adopt additional policies for energy conservation and climate changes from 2010. The average annual growth rate of the terminal electricity consumption will reach 10.5% from 2011 to 2015, and 11.0% from 2016 to 2020. The power structure, thermal power generation efficiency and line loss rate remains the same as that in 2010.
	Current policy scenario	The current policy scenario is mainly based on the existing development plans and policies issued in the electricity sector, including the “12th Five-Year Plan” of energy development and the “12th Five-Year Plan” of renewable energy development.
	Low-carbon policy	The low-carbon policy scenario is more optimistic by adopting more radical

	scenario	policies to promote low-carbon development in the electricity sector.
[95]	BAU	Mainly thermal power; Binding conditions not including carbon emissions; Ultra-supercritical (USC), Air cooling technology and New energy technology (later); Maintaining the energy policy before 11th Five-Year Plan; Execute the electrovalence policy before 2009.
	Mitigation scenario	Stress on structural adjustments, and develop clean energy and renewables. Renewable energy over 15% by 2020 is a binding condition. USC, onshore wind power, offshore wind power, nuclear and biomass will be developed. There are some positive industrial policies and supporting measures to encourage rapid development of low carbon energy.
[96]	Reference scenario	No carbon tax.
	Scenario 1	Moderate carbon tax only in the cement sector.
	Scenario 2	High carbon tax only in the cement sector.
	Scenario 3	Moderate carbon tax in all industries.
	Scenario 4	High carbon tax in all industries.
[97]	BAU	The growth rates of economic activity, industrial structure, electricity intensity, generation structure and energy intensity are average annual growth rates during 1997-2014.
	ED (economy-driven)1	Economy-driven (Single aspect) scenario 1. The Chinese government can keep the increasing speed of GDP per capita. Indutsrial structure and electricity intensity maintain their average annual decrease rates in 1997-2014. Generation structure and energy intensity maintain 80% of their average annual decrease rate in 1997-2014.
	ED2	Economy-driven (Single aspect) scenario 2. The Chinese government can keep the increasing speed of GDP per capita. The industrial structure and electricity intensity maintain 80% of their average annual decrease rates, and generation structure and energy intensity maintain the average annual decrease rates in the research period.
	ED3	Economy-driven (Single aspect) scenario 3. The Chinese government tries to lower the increase speed of annual per-unit GDP with 80% growth rate as before. The economic activity, generation structure and energy intensity maintain 80% of their average annual decrease rates in BAU. The industrial structure and electricity intensity maintain 100% of their average annual decrease rates in BAU.
	ED4	Economy-driven (Single aspect) scenario 4. The Chinese government tries to lower the increase speed of annual per-unit GDP with 80% growth rate as before. The economic activity, industrial structure and electricity intensity maintain 80% of their average annual decrease rates in BAU. The generation structure and energy intensity maintain 100% of their average annual decrease rates in BAU.
	ESD (economic structure-driven)1	Economic structure-driven (Single aspect) scenario 1. The industrial structure and electricity intensity maintain 120% of their average annual decrease rates in BAU. The generation structure and energy intensity maintain 80% of their average annual decrease rates in BAU. The GDP per capita maintains 100% of its average annual growth rate.
	ESD2	Economic structure-driven (Single aspect) scenario 2. The GDP per capita maintains 80% of its average annual growth rates in BAU. The industrial structure and electricity intensity maintain 120% of their average annual decrease rates in BAU. The generation structure and energy intensity maintain

		their decrease rates in BAU.
	EED1	Energy efficiency-driven (Single aspect) scenario 1. The GDP per capita maintains 100% of its average annual growth rates in BAU. The industrial structure and electricity intensity maintain 80% of their average annual growth rates in BAU. The generation structure and energy intensity maintain 120% of their average annual growth rates in BAU.
	EED2	Energy efficiency-driven (Single aspect) scenario 2. The GDP per capita maintains 80% of its average annual growth rates in BAU. The industrial structure and electricity intensity maintain 100% of their average annual decrease rates in BAU. The generation structure and energy intensity maintain 120% of their average annual decrease rates in BAU.
	EESD (Economy& Economic structure-driven)1	Economy & Economic structure-driven (Double-aspects) 1. The GDP per capita maintains 100% of its average annual growth rate in BAU. The industrial structure and electricity intensity maintain 120% of their average annual decrease rates in BAU. The generation structure and energy intensity maintain 80% of their average annual decrease rates in BAU.
	EESD2	Economy & Economic structure-driven (Double-aspects) 2. The GDP per capita, generation structure and energy intensity maintain 100% of their average annual change rates in BAU. The industrial structure and electricity intensity maintain 120% of their average annual decrease rates in BAU.
	EEED1	Economy & Energy efficiency-driven (Double-aspects) 1. The GDP per capita maintains 100% of its average annual growth rate in BAU. The industrial structure and electricity intensity maintain 80% of their average annual decrease rates in BAU. The generation structure and energy intensity maintain 120% of their average annual decrease rates in BAU.
	EEED2	Economy & Energy efficiency-driven (Double-aspects) 2. The GDP per capita, industrial structure and electricity intensity maintain 100% of their average annual change rates in BAU. The generation structure and energy intensity maintain 120% of their average annual decrease rates in BAU.
	ESEED1	Industrial structure & Energy efficiency-driven (Double-aspects) 1. The GDP per capita maintains 80% of its average annual growth rate in BAU. The industrial structure, electricity intensity, generation structure and energy intensity maintain 120% of their average annual decrease rates in BAU.
	ESEED2	Industrial structure & Energy efficiency-driven (Double-aspects) 2. The GDP per capita maintains 100% of its average annual growth rate in BAU. The industrial structure, electricity intensity, generation structure and energy intensity maintain 120% of their average annual decrease rates in BAU.
[98]	BAU	The growth rates of emission coefficient, energy structure, energy intensity, industrial structure, industrial value added and energy price are the same as the annual average growth rates of 1996-2012.
	Middle scenario	The growth rates of energy intensity, industrial value added and energy price are the intermediate values of BAU and advanced scenario. The growth rates of emission coefficient, energy structure and industrial structure are the same as BAU.
	Advanced scenario	The expected annual economic growth rate is 7% and the growth rate of energy intensity is set by the reduction target of 16% in 2015 compared to 2010. The energy price is set according to Lin and Zhao (2014). The growth rates of emission coefficient, energy structure and industrial structure are the same as BAU.
[99]	BAU	Under BAU, each variable (energy substitution, labor productivity, technology

		and producer price index of energy products) will still maintain the annual average growth rate over 2011-2020
	Moderate	The moderate scenario is between the BAU and the advanced scenarios. The future growth rate of the variables in the moderate scenario is the average value of the BAU scenario and the advanced scenario.
	Advanced	The advanced scenario means the best situation of CO_2 emissions reduction including the most active carbon-reduction policies. The highest historical values observed are regarded as the future growth rate of each variable.
[100]	Scenario 1	Power industry develops at a high speed and the technical structure is adjusted at a high speed.
	Scenario 2	Power industry develops at a low speed and the technical structure is adjusted at a low speed. Industrial structure, electricity, generation structure and energy intensity maintain 120% of their average annual growth rate in BAU.
[101]	Technology 1	Coal moisture control
	Technology 2	Coke dry quenching
	Technology 3	Generating of sinter waste heat
	Technology 4	Preheat of sinter plant
	Technology 5	Improved process control
	Technology 6	Generating
	Technology 7	Top gas recovery turbine unit
	Technology 8	Recovery of blast furnace gas
	Technology 9	Blast furnace control
	Technology 10	Recuperator on the hot blast stove
	Technology 11	Pulverised coal injection
	Technology 12	Combine cycle power plant
	Technology 13	Heat recovery of BOF gas
	Technology 14	Flue gas waste heat recovery
	Technology 15	Continuous casting
	Technology 16	Recuperative burners
	Technology 17	Process control in hot strip mill
	Technology 18	Insulation of furnaces
	Technology 19	Waste heat recovery
	Technology 20	Heat recovery on annealing line
	Technology 21	Automated monitoring and targeting system
	Technology 22	Continuous annealing
	Technology 23	Flue gas desulphurisation
	Technology 24	Flue gas denitrification
[102]	Basic	The basic scenario is set based on the historical changes and the mandatory planning of the country.

	Moderate scenario	The moderate scenario is considered as the average case within a moderate policy path.
	Optimum scenario	The optimum scenario represents the strongest scenario when the Chinese government would make an utmost effort to reduce carbon emissions in the power industry.
[103]	BAU	This study predicted the CO_2 emissions of each region from 2013 to 2020 using a second-order polynomial generated in line with these regions' CO_2 emissions levels between 2000 and 2012.
[104]	Baseline	According to the NDRC (National Development and Reform Commission), NEA (National Energy Administration) and CEC (China Electricity Council), in 2020 China's total installation of electricity generation will reach 1943 GW, with 61.91% will be by thermal power (1203 GW).
	Ambitious scenario	The ambitious scenario considers the improved potential of energy efficiency and the installation potential of alternative energy resources.
[105]	Scenario 1	Scenario 1 is based on the average growth rate of each factor during 1991-2012.
	Scenario 2	Scenario 2 is a higher-emission scenario based on the growth rates of factors 1% higher that those in Scenario1.
	Scenario 3	Scenario 3 is a lower-emission scenario based on the growth rates of factors 1% lower than those in Scenario 1.
[106]	BAU	The growth rates of output, energy intensity and emission coefficient under the BAU scenario based on the historical trend during the period 2001–2013.
	2020 target scenario	The growth rate of emission coefficient is based on the average growth rate during 2011-2013. The growth rate of energy intensity is from the decrease 45% in 2020 compared with 2005.
	2030 target scenario	To further reduce carbon coefficient from 2020 to 2030.
[107]	BAU	No emission reduction target and the development pathway of technology depends entirely on relative costs and benefits
	SRT (Single emissions reduction) scenario	Lower carbon intensity of cement output.
	MRT (Multiple emissions reduction) scenario	Long-term is the same as SRT scenario while the mid-term carbon intensity of cement output is higher than that in SRT scenario.
[108]	BAU	BAU is established based on the historical development of each factor (1990-2014).
	Ideal Scenario	Maximize the negative driving factors and minimize the positive factors.
[109]	Energy conservation scenario1	The industrial growth rate is 4% and the nergy consumption growth rate is 0.9%.
	Energy conservation scenario2	The industrial growth rate is 6% and the energy consumption growth rate is 2.8%.
	Energy conservation scenario3	The industrial growth rate is 8% and the energy consumption growth rate is 4.8%.
	Energy conservation scenario4	The industrial growth rate is 10% and the energy consumption growth rate is 6.7%.

[110]	Base Renewable Mandatory Market Share (MMS) with Equal Shares Dispatch Scenario	Macroeconomic parameters (GDP, population and urbanization) are assumed to be the same for all scenarios. The baseline scenario reflects the 2010 outlook on renewable power development and continued use of the existing “equal-shares” generation dispatch through 2050, assuming no new policies to successfully resolve curtailment and renewable dispatch barriers are adopted through 2050.
	Base Renewable MMS with Green Dispatch Scenario	China continues to pursue renewable energy development following the revised 2011 renewable capacity targets and assumes successful implementation of green dispatch as a result of supporting policies adopted since 2011.
	Strengthened Renewable MMS with Green Dispatch Scenario	China adopts more aggressive renewable energy capacity build-out to meet the new non-fossil targets and successfully implements green dispatch.
	Baseline Scenario	Assumes no adoption of CCS technologies in the power sector through 2050 due to existing barriers to scale up and commercialization in the absence of additional policies.
	Base CCS Policy Scenario	It assumes commercialization of CCS after 2030 with accelerate growth of post-combustion CCS installed capacity to a level capable of sequestering 500 $MtCO_2$/year by 2050 based on the NDRC (National Development and Reform Commission) and ADB (Asian Development Bank) Roadmap analysis.
	Accelerated CCS Policy Scenario	It assumes more aggressive CCS deployment after 2030, resulting in doubling of post-combustion CCS installed capacity capable of sequestering 1000 $MtCO_2$/year by 2050.
	Baseline Coal-fired Efficiency Scenario	It assumes continuation of the early-retirement policies for small inefficient coal-fired generation initiated during the 11th FYP period.
	Accelerated Coal-fired Efficiency Scenario	It assumes policies in support of the 2014-2020 Action Plan mandating faster retirement of small and medium-sized subcritical units are successful. To accelerate the adoption of efficient supercritical and ultra-supercritical coal-fired generation, with no new units of less than 600 MW capacity after 2020.
[111]	BAU	The BAU scenario is the maintenance scenario: the technical, economic, and policy environments in the period 2012-2020 are similar to those in the period 2005-2012.
	Planned scenario	The development of economic factors are based on the related document from the government.
[112]	Baseline scenario	Assuming that existing policies on energy and environment will be continued and implemented. Technology progress keeps at a moderate level. International trading will increase and China’s economy will be integrated further into the global economy. The growth rate of total GDP (in constant 2000 USDs) is 8% between 2000 and 2030, while total population would increase by 15%. The total primary energy consumption is estimated to increase by 3.2% between 2005 and 2030. The consumption of coal is projected to grow by 80%, mainly for fuel power generation. Oil demand is expected to grow by 160%, and renewable energy increase by 4%.
[113]	BAU	The growth rates of the variables (energy intensity, labor productivity and industrial scale) are the same as the historical trend. The growth rate of energy intensity is -4.23%. The growth rate of labor productivity is at 11.43% before 2020, 10.93% in the period 2021-2025 and 10.43% in the period 2025-2030; The growth rate of industrial structure is 2.39% until 2030.

	Moderate	Many moderate emission reduction measures will be taken in this scenario. The growth rate of energy intensity is -6.63%; The growth rate of labor productivity is the same as Scenario 1. The growth rate of industrial scale is 2.19%.
	Advanced	Many advanced measures will be taken in this scenario. The growth rate of energy intensity is -8.52%; The growth rate of labor productivity is the same as Scenario 1. The growth rate of industrial scale is 1.99%.
[114]	The technology frozen scenario (TFS)	Diffusion rates of all the considered technologies are assumed as the same as the benchmark year of 2014.
	BAU	The BAU scenario is where the adoption of technologies continues in line with historical trends.
	Scenario 1	In addition to the same technologies used in BAU, a carbon price of 60 Yuan/t-CO_2 imposed in China is consumed.
	Scenario 2	In addition to the same technologies used in BAU, a carbon price of 100 Yuan/t-CO_2 imposed in China is consumed.
[115]	Baseline	This scenario assumes that electricity consumption, non-fossil energy, and thermal power generation will continue to follow their past development trends in 2016-2030. No significant electric technological progress, policy adjustment and socioeconomic changes occur during this period.
	Scenario 2	Growth rate of electricity consumption is 80% of baseline.
	Scenario 3	Growth rate of non-fossil energy use is 120% of baseline.
	Scenario 4	Growth rate of thermal power generation efficiency is 120% of baseline.
	Scenario 5	Scenario 2, 3 and 4 happen together.
[116]	BAU	BAU scenario will emphasize the future situation of China's iron and steel sector without additional measures.
	CEC (Cut excessive industrial capacity) scenario	The CEC scenario is based on China's 13th FYP and "Views on resolving overcapacity of iron and steel industry and poverty alleviation". Crude steel production capacity reduced from 2016 to 2020. China's economy will face a slightly slower growth, and the economic structure in China has changed.
	TI (technology improvement) scenario	Crude steel production capacity is the same as BAU. The technical promotion is encouraged. The proportion of the short-process electric arc furnace is the same with CEC scenario.
	ET (Emission trade) scenario	Crude steel production capacity is the same as ECE scenario. Technical promotion is the same as TI scenario.
[117]	Baseline (S1)	There is no imported scrap use. The annual growth rate of scrap ratio is 10.7% from 2014 to 2030.
	The current policy scenario (S2)	Low imported scrap ia used. The steel scrap is divided into domestic and imported scrap. The changing trends in steel scrap imports are based on the situation between 2000 and 2014.
	The new policy scenario (S3)	High imported scrap is used. Through substantial steel scrap importing, the scrap ratio is kept at 0.35 (optimal scrap ratio).
[118]	BAU	Efficiency improvement and structural adjustment are based on the targets of existing policies.
	N1	Strong structural adjustment & High efficiency improvement.

	N2	Structural adjustment at baseline level & High efficiency improvement.
	N3	Strong structural adjustment & Efficiency improvement at baseline level.
	N4	Structural adjustment & efficiency improvement are at baseline levels, where baseline level is the historical trends in structural adjustment and efficiency improvement.
[119]	NTES	No special technical progress happens in all sectors
	CTES	Special technical progress among all sectors, with direct carbon intensity decreasing at by 10%.
	CTES	Special technical progress among all sectors, with direct carbon intensity decreasing at by 20%.
	CTES	Special technical progress among all sectors, with direct carbon intensity decreasing at by 30%.
	DTES	All sectors are categorized into four types, with direct carbon intensity of low-carbon cluster decreasing 30%.
	DTES	All sectors are categorized into four types, with direct carbon intensity of whole-process high-carbon cluster decreasing 30%. conductive high-carbon, apparent high-carbon.
	DTES	All sectors are categorized into four types, with direct carbon intensity of conductive high-carbon cluster decreasing 30%.
	DTES	All sectors are categorized into four types, with direct carbon intensity of apparent high-carbon cluster decreasing 30%.
[120]	BAU	Maintain the average growth rate from 1985 to 2013.
	Ideal scenario	Maximize the negative driving factors and minimize the positive factors.
	Current policy scenario	Present or accessible policy implementation and development situation.
[121]	Baseline scenario (BS)	Maintain the current trends in energy intensity, process emission factors, clinker-to-cement ratios and the use of alternative materials from 1980 to 2014.
	A best practice scenario (BPS)	With respect to the use of alternative wastes and the application of 31 energy-saving measures.
[122]	HLL	High decline proportion of heavy chemical industry newly added capacity rate; Low carbon price; and Low annual carbon allowance distribution amount.
	HMM	High decline proportion of heavy chemical industry newly added capacity rate; Medium carbon price; and Medium annual carbon allowance distribution amount.
	HHH	High decline proportion of heavy chemical industry newly added capacity rate; High carbon price; and High annual carbon allowance distribution amount.
	MLL	Medium decline proportion of heavy chemical industry newly added capacity rate; Low carbon price; and Low annual carbon allowance distribution amount.
	MMM	Medium decline proportion of heavy chemical industry newly added capacity rate; Medium carbon price; and Medium annual carbon allowance distribution amount.
	MHH	Medium decline proportion of heavy chemical industry newly added capacity rate; High carbon price; and High annual carbon allowance distribution

		amount.
	LLL	Low decline proportion of heavy chemical industry newly added capacity rate; Low carbon price; and Low annual carbon allowance distribution amount.
	LMM	Low decline proportion of heavy chemical industry newly added capacity rate; Medium carbon price; and Medium annual carbon allowance distribution amount.
	LHH	Low decline proportion of heavy chemical industry newly added capacity rate; High carbon price; and High annual carbon allowance distribution amount.
[123]	Benchmark scenario	The growth rates of industrial value added, industrial structure, energy intensity and energy structure are the same as annual average growth rates of historical data.
	Energy-saving scenario	The growth rate of industrial value added is lower than the benchmark. The growth rate of industrial structure is the same with the benchmark. The decrease rate of energy intensity is higher than the benchmark. The energy-saving growth rate of energy consumption is higher than the benchmark.
[124]	BAU	The power sector performance stays as observed in year 2015 without any new mandates happening in this scenario.
	Pressimistic policy scenario	The "pessimistic policy" assumptions correspond to the least stringent rules that could be enacted for a particular policy.
	Median policy scenario	The "median policy" assumptions reflect the average of the pessimistic and optimistic ones.
	Optimistic policy scenario	The "optimistic" correspond to the most stringent policy mix.
[125]	A reference scenario	A continuation of the existing policies in China's cement sector over the next 40 years without imposing any additional energy-saving or emission-reduction targets. This scenario is established and calibrated against the annual production, energy consumption and carbon emissions.
	Carbon tax (CT) 1	Carbon tax will be imposed on CO_2 emissions from the entire energy system. Carbon tax will be \$20 in 2020 and \$86 in 2050.
	CT2	Carbon tax will be imposed on CO_2 emissions from the entire energy system. Carbon tax will be \$30 in 2020 and \$129 in 2050
	CT3	Carbon tax will be imposed on CO_2 emissions from the entire energy system. Carbon tax will be \$50 in 2020 and \$215 in 2050.
[126]	Base scenario	All factors (carbon intensity, energy structure, energy intensity, economic output and population size) are set according to historical trends.
	Scenario 1	The growth rate of energy structure is lower than base scenario. Other factors are the same as base scenario.
	Scenario 2	The growth rate of energy structure is lower than scenario 1. Other factors are the same as base scenario.
	Scenario 3	The decline rate of energy intensity is lower than base scenario. Other factors are the same as base scenario.
	Scenario 4	The decline rate of energy intensity is lower than scenario 1. Other factors are the same as base scenario.
	Scenario 5	The growth rate of population is lower than base scenario. Other factors are the same as base scenario.

	Scenario 6	The growth rate of population is lower than scenario 1. Other factors are the same as base scenario.
	Scenario 7	The growth rate of energy structure is the same as scenario 1. The decline rate of energy intensity is the same s scenario 3. The growth rate of population is the same as scenario 5.
	Scenario 8	The growth rate of energy structure is the same as scenario 2. The decline rate of energy intensity is the same s scenario 4. The growth rate of population is the same as scenario 6.
[127]	BAU	Include existing major policies.
	PS (production structure) scenario	Adjust the production structure.
	LT (low-carbon technology) scenario	Promote low-carbon technologies on the basis of PS scenario
	CF (clean fuels) scenario	Switch to clean fuels on the basis of LT scenario
[128]	High production scenario	The annual production growth rates of aluminum and copper industries will decline 30% in two periods 2021-2025 and 2026-2030.
	Low production scenario	The annual production growth rates of aluminum and copper industries will decline 50% in two periods 2021-2025 and 2026-2030.
[129]	Scenario 1	BAU Calcination-related CO_2 emissions; BAU Combustion-based CO_2 emissions; BAU Electricity-related CO_2 emissions.
	Scenario 2	BAU Calcination-related CO_2 emissions; BAU Combustion-based CO_2 emissions; BP Electricity-related CO_2 emissions.
	Scenario 3	BAU Calcination-related CO_2 emissions; BP Combustion-based CO_2 emissions; BAU Electricity-related CO_2 emissions.
	Scenario 4	BAU Calcination-related CO_2 emissions; BP Combustion-based CO_2 emissions; BP Electricity-related CO_2 emissions.
	Scenario 5	BP Calcination-related CO_2 emissions; BAU Combustion-based CO_2 emissions; BP Electricity-related CO_2 emissions.
	Scenario 6	BP Calcination-related CO_2 emissions; BP Combustion-based CO_2 emissions; BAU Electricity-related CO_2 emissions.
	Scenario 7	BP Calcination-related CO_2 emissions; BP Combustion-based CO_2 emissions; BP Electricity-related CO_2 emissions.
[130]	BAU scenario	A continuation of the existing trends will occur. The production structure and the share of EAF (electric arc furnace) steel production will maintain the level of 2015. The implementation rate of ESTs (energy saving technologies) will increase 1.0% and 2.0% per year during 2010-2030 and 2030-2050.
	Structure adjustment (STA) scenario	In the STA scenario, the ratio of pig iron used as feedstock in EAF and the share of EAF steel production have been adjusted. The implementation rate of ESTs is the same as that of the BAU scenario.
	The energy-efficiency improvement (EEI) scenario	Compared with the BAU scenario, the EEI scenario has a higher implementation rate of ESTs. The implementation rate of ESTs will increase 3% and 4% per year during 2010-2030 and 2030-2050, respectively.
	The strengthened policy (STP) scenario	Integrate the effects of production adjustment and ESTs, aiming to evaluate the largest energy saving and emissions mitigation potential.

[131]	Reference scenario	Key features in this scenario are the absence of climate policy intervention and the low requirement of high energy-intensive de-capacity (HEI) in the industrial sector.
	Low-carbon scenario	Key features are climate policy interventions and high HEI capacity and industrial adjustment and optimization requirements.
[132]	BAU	Economic growth is the key driving factor of the increase in CO_2 emissions without considering economic policy changes and structural adjustment. The carbon tax and emissions trading system are not introduced during 2010-2050.
	CT10	Carbon tax is included in this scenario, 10 yuan/ton.
	CT30	Carbon tax is included in this scenario, 30 yuan/ton.
	CT50	Carbon tax is included in this scenario, 50 yuan/ton.
	CTP	Carbon tax is included in this scenario, 10 yuan/ton in 2020, 50 yuan/ton and increase by 5.51% every year.
	ETPA	Partial sectors are introduced into ETS, and the quota allocation is auction.
	ETPF	Partial sectors are introduced into ETS, and the quota allocation is free allocation.
	ETAA	All sectors are introduced into ETS, and the quota allocation is auction.
	ETAF	All sectors are introduced into ETS, and the quota allocation is free allocation.
	CT30ETPA	Carbon tax is included in this scenario, 30 yuan/ton. Partial sectors are introduced into ETS, and the quota allocation is auction.
	CT30ETPF	Carbon tax is included in this scenario, 30 yuan/ton. Partial sectors are introduced into ETS, and the quota allocation is free allocation.
	CT30ETAA	Carbon tax is included in this scenario, 30 yuan/ton. All sectors are introduced into ETS, and the quota allocation is auction.
	CT30ETAF	Carbon tax is included in this scenario, 30 yuan/ton. All sectors are introduced into ETS, and the quota allocation is free allocation.
[133]	Base scenario	Parameters constraint include fuel consumption rates of power plants, per unit capital cost for construction of power plants, capacity shrinking coefficient retrofit of coal-fired and IGCC (integrated gasification combined cycle plants) plants, per unit cost of retrofitting of PC (coal-fired plants) and IGCC plants, power demand, expected lifetimes of power plants, annual operating time of power plants, cap for CO_2 emissions, carbon price, emission coefficient, Operation-and-Maintenance costs of power plants. The details of these parameters can be found in this paper.
	Peak scenario	Considering the need for grid peak load regulation and stabilization, it is assumed that NGCC (natural gas combined cycle plants) power plants should take at least a share of 10% in the total power capacity in the grid, on the basis of base scenario.
[134]	BAU	The minimum close down capacity of coal-fired plants every five years is 20 GW.
	Medium-speed scenario	The minimum close down capacity of coal-fired plants every five years is 20 GW. The carbon capture and storage will be introduced in 2025. The minimum carbon capture volume is 160 Mt.
	High-speed scenario	The minimum close down capacity of coal-fired plants every five years is 20 GW. The carbon capture and storage will be introduced in 2020. The minimum

		carbon capture volume is 160 Mt.
[135]	Scenario 1	GEP (Generation Expansion Planning) and TEP (Transmission Expansion Planning) are conducted separately. TEP is executed after GEP according to the practical situation in China.
	Scenario 2	GEP and TEP are carried out together, which can be regarded as an integrated source-grid planning.
	Scenario 3	The integrated source-grid-load planning is carried out.

Table A8. The scenario assumptions of the optimistic scenarios in Fig.5 of the main body.

Sectors	Parameters						
	Emission coefficient	Energy intensity	Energy mix	Industrial structure	Industrial activity	CCS	Others
Industrial sector		The costs of emissions-reducing technologies are available below \$20/tCO_2, as opposed to \$100/tCO_2 under BAU from 2005 to 2020 [72]; the energy intensity of high-energy consumption sub-sectors decreases annually between 3.9%-4.4% from 2013 to 2030, while it increases at 0.53% annually under BAU [98]; the energy price increases annually by 10% from 2013 to 2020 and 11% from 2021 to 2030, while it decreases by 0.26-0.43% under BAU [98]; high efficiency improvement [118].		Strong shifts in industrial structure [118].	The growth rate of IVA is lower than BAU from 2013 to 2030 [98].		
Electricity		The electrical efficiencies of power plants are 2% higher than BAU [66]; The technical losses due to transmission, distribution and own use of power plants are reduced by 1/3 relative to the 2020 BAU level [66]; The dispatch is improved [75]. 40% decrease in carbon intensity by 2030 on the basis of 2010 [75]. Efficiency and emissions standards preventing the refurbishment of old inefficient plants [136]. RD&D	Use of renewables (including large hydropower) is higher than in the BAU scenario in 2020 [66].The remaining coal and oil used in power plants in 2020 in China is assumed to be replaced by natural gas [66]. The installed capacity of wind and nuclear is 220 GW and 140 GW in 2030, respectively [75]. Carbon price is 23,4 /tCO_2 until		Demand for electricity is 30% lower than BAU [66].	Expanded support for the deployment of CCS [136]. The IGCC and CCS is introduced in 2015 [75].	Stringent emissions limits for industrial facilities above 50 MWth input using solid fuels, set at 200 mg/m3 for SO_2 and NO_X and 30 mg/m3 for

	on innovative technologies and support to innovative market designs [136].	2030 [75]. Increased low-carbon generation from renewables and nuclear [136].				PM2.5 [136].
Ferrous metals	Energy efficiency improvement ratio per annum is 3‰ in 2010 and it will be 3.5‰ in 2020 [70]. The proportion of short-process electric arc furnace steelmaking would increase from 6.1% in 2014 to 25.6% in 2040 [116]. Strong technical promotion from 2016 to 2040 [116]. The penetration rate of energy-saving technologies will reach 90% and 70% for key and non-key producers, respectively, in 2050 [80]. The pulverized coal injection will reach the international advanced level of 200 kg/t [80].					
Non-metallic products	The thermal efficiency is to reach much below 2.5 GJ/t clinker [87].	A fuel composition should be with 70% substitution [87].		Cement production is 1580 on 2015 and 1170 in 2020, which is almost 1/3 lower	40% of cement production should be equipped with CCS	

				than BAU [73]. The average clinker ratio should be 50% [87].	[87].	
Chemicals		The energy efficiency growth rate should be 11.8% (7.3% in BAU) [82]; the energy price growth rate should be 20% from 2012 to 2020 (8% in BAU) [82].		The company scale growth rate should be 12.8% (9.8% in BAU) [82]; the growth rate of added value of output is 13% from 2012 to 2020 (12.5% in BAU) [82].		
Petroleum	The change rate of emission coefficient is -0.84% from 2014 to 2020 and -1.37% from 2020 to 2030 (-0.36% since 2014 in the BAU) [106].	The change rate of energy intensity is -3.09% from 2014 to 2030 (-3.64% since 2014 in BAU) [106].		The growth rate of output is 8% from 2014 to 2030 (10.29% in BAU) [106].		
Non-ferrous metals				The annual growth rates of production in aluminum and copper will decline by 50% from 2020 to 2030 [128].		
Energy-intensive industries			The carbon price is 7.25 $/tCO_2$ from 2017 to 2020	The change rate of output is -2%		Annual carbon

	(5.8 $/tCO$_2$ in BAU), 11.6 $/tCO$_2$ from 2021 to 2025 (10.15 $/tCO$_2$ in BAU) and 14.5 $/tCO$_2$ from 2026 to 2030 (13.05 $/tCO$_2$ in BAU) [122].	from 2017 to 2020 and -1% from 2021 to 2030 [122].	allowance is 40 Mt 2017 to 2020 (35 Mt in BAU), 70 Mt from 2021 to 2025 (65 Mt in BAU), and 90 Mt from 2026 to 2030 (85 Mt in BAU) [122].

5. Detailed information on policies related to the climate change

China has a tradition of frequent and detailed government-mandated policies. In this section, we collected the policies concerning climate change, energy conservation, industrial structure, and energy structure enacted since 2001. Tables A9-12 are the full list of these policies. Some major targets of industrial sector were also presented visually in Fig.A2. The share of industrial value added in GDP and the future GDP are shown in Table A13. This section is related to section 5.5 of the main body.

Table A9. General policies related to climate change and energy efficiency at national level (multi-industries including industrial sector).

Policy Title	Year	Policy Status	Policy targets
Energy Supply and Consumption Revolution Strategy (2016-2030)	2017	In Force	The policies mainly focus on the energy sector. Energy structure, energy intensity and energy demand until 2020, 2030 and 2050 are regulated. The energy-related CO_2 emissions and carbon intensity up to 2030 are also regulated. URL:http://www.sdpc.gov.cn/gzdt/201704/t20170425_845304.html
The 13th Five-Year Plan For Economic and Social Development of The People's Republic of China (2016-2020)	2017	In Force	Climate-related subjects, ecosystems and the environmental impacts are discussed. URL:http://en.ndrc.gov.cn/newsrelease/201612/P020161207645765233498.pdf
Nationally Determined Contribution (NDC) to the Paris Agreement: China	2015	In Force	The targets related to the peaking of CO_2 emissions, carbon intensity reduction, energy structure and forest stock are promised through "nationally determined contributions". URL:http://unfccc.int/focus/ndc_registry/items/9433.php
Energy efficiency Leader Scheme	2015	In Force	The program aims to set up a long-term mechanism to incentivise energy-efficient "leaders", such as manufacturers and brands that exceed specific energy-efficiency benchmarks set by the China Energy Label. URL:http://www.miit.gov.cn/n11293472/n11293832/n12843926/n13917012/16400095.html
Action Plan for retrofitting and upgrading coal-fired power plants (2014-2020)	2014	In Force	The plan strengthens the energy efficiency and pollutants emission standards applied to coal power plants. The coal power plants with the capacity of over 600 MW are required to achieve the efficiency target of 300g of coal equivalent/kWh by 2020. URL:http://www.sdpc.gov.cn/zcfb/zcfbtz/201409/t20140919_626235.html
Strategic Action Plan for Energy Development (2014-2020)	2014	In force	The targets of annual primary energy consumption, coal consumption and efficiency of coal-power plants by 2020 have been set. The expansion of high-pollution and high energy-intensive industries is heavily restricted, alongside the phase-out of obsolete technologies and excess capacity. URL: http://www.gov.cn/zhengce/content/2014-11/19/content_9222.htm
Plan for accelerating the development of energy conservation and environmental	2013	In force	The plan aims to promote the industrialization and local manufacturing of energy efficient and clean energy technologies such as boilers, motors, regenerative combustion technology, new energy vehicles, and semi-conductor lighting.

protection related industries			URL: http://www.gov.cn/zwgk/2013-08/11/content_2464241.htm
The National Plan for Addressing Climate Change (2014-2020)	2013	In Force	This Strategy specifies the guiding thoughts and principles in adapting to climate change on a national level by 2020. Policies related to climate change are industrial structure adjustment, energy conservation, energy efficiency improvement, energy structure optimization, emissions from non-energy activity control and carbon sink increase. URL: http://en.ccchina.gov.cn/archiver/ccchinaen/UpFile/Files/Default/20141126133727751798.pdf
Interim Measures for the Administration of Voluntary Greenhouse Gas Emission Reduction Trading	2013	In Force	The pilot of emissions trading system are established in five major cities and two provinces. This measure can achieve emissions reduction through market mechanism. URL: http://cdm.ccchina.gov.cn/ccer.aspx
The 12th Five-Year Plan For Economic and Social Development of The People's Republic of China (2011-2015)	2011	Superseded	This plan includes binding energy targets, such as the share of non-fossil fuels and energy intensity reduction target. The development of new energy industries and the renewable energies are also regulated. URL: http://www.moa.gov.cn/fwllm/jjps/201103/t20110317_1949003.htm
China's Copenhagen Accord Pledge	2010	In Force	Carbon intensity reduction, the share of non-fossil fuel in primary energy consumption and forest coverage are included. URL:http://unfccc.int/meetings/copenhagen_dec_2009/items/5262.php
Demand-Side Management Implementation Measures	2010	In Force	The policy supports incentives for pricing at peaks, seasonal pricing, reliability pricing, and interruptible load pricing. URL: https://www.nrdc.org/sites/default/files/dsm.pdf
China's National Climate Change Program	2007	In Force	The strategy is to address climate change and sustainable development, including economic restructuring, energy efficiency improvement, vehicle emission standards, participation in international R&D programs, development & utilization of hydropower and other renewable energy, ecological restoration & protection and family planning. URL:http://en.ndrc.gov.cn/newsrelease/200706/P020070604561191006823.pdf
Strategic Plan for Industrial Efficiency	2006	In force	Within the 11th FYP, China's strategic plan for energy efficient industrial processes involves equipment renovation and the design and implementation of process optimization and management measures. Targeting the metallurgical industry, petrochemical industry, and chemical industry, the Chinese state aims to improve energy efficiency and industrial competitiveness to "the highest level or close to the worlds front-runners". URL: http://ghs.ndrc.gov.cn/15ghgy/t20060529_70793.htm
Conversion of Exhaust Heat and Pressure	2006	In force	Within the 11th Five Year Period (2006-2010), the Chinese government has mandated the efficient use of exhaust, pressure and heat from mining and industrial processes. Detailed plan is targeted to iron and steel enterprises, concrete production lines and ground coalbed gas (CBG). URL: http://en.ndrc.gov.cn/newsrelease/200603/t20060323_63813.ht

			ml
Top 1000 Industrial Energy Conservation Program	2006	In Force	This program is to promote energy conservation in industrial enterprises. URL:http://www.ndrc.gov.cn/rdzt/jsjyxsh/200604/t20060413_66114.html
The 11th Five-Year Plan For Economic and Social Development of The People's Republic of China (2006-2010)	2006	Superseded	This Plan has some commitments related to environment and climate change, such as economic growth, economic structure, population, resources & environment, energy intensity reduction; renewable energy, fuel standards, Energy Efficiency Light Bulb Program, Retirement of Inefficient Plants and Aluminum Industry Permit Standards. URL:http://en.ndrc.gov.cn/newsrelease/200603/t20060323_63813.html
General Work Plan for Energy Conservation and Pollutant Discharge Reduction	2006	In Force	This plan is used to cut energy intensity and major industrial pollutants. The industrial materials included are electricity, steel, nonferrous metals, construction materials and oil processing and chemicals. URL: http://www.gov.cn/english/2007-06/03/content_634537.html
Asia-Pacific Partnership for Clean Development and Climate	2005	In Force	This is a program that partner countries agree to co-operate on development and transfer of technology which enables reduction of GHG. Eight taskforces are included, such as aluminum, buildings & appliances, cement, coal mining, steel, cleaner fossil energy, renewable energy & distribution generation and Power generation & transmission. URL:http://www.asiapacificpartnership.org/
China Energy Label Law	2004	In Force	The energy efficiency label should be attached with electronic appliances. URL:http://www.energylabel.gov.cn/en/PoliciesandRegulations/index.html
Medium and Long-term Plan of Energy Conservation: 10 Energy Conservation Programs	2004	In Force	This Plan covers the 2005-10 and the 2010-20 period. It details energy conservation aims and implementation plans to be undertaken during the 11th five year period (2006-2010) and beyond. Ten programs are included. URL: http://en.ndrc.gov.cn/
The Trial Implementation of Differential Pricing Policy in 6 High Energy-intensive Industries (2004-2012)	2004	In Force	The Chinese government has imposed a differential energy pricing scheme for high energy-consuming industries and products to promote energy conservation. URL:http://www.sciencedirect.com/science/article/pii/S0301421512001668
Australia - China Bilateral Cooperation on Climate Change (MOU)	2003	In Force	Five climate change projects are set out in the Joint Declaration on Bilateral Cooperation on Climate Change, including climate change policies, climate change impacts & adaptation, national communication, technology cooperation and capacity building & public awareness. URL:http://www.deh.gov.au/minister/env/2003/mr24oct203.html
The 10th Five-Year Plan For Economic and Social Development of The People's	2001	Ended	The principle objectives of this plan related to climate change are sufficient utilization of clean energies, promoting new energy and renewable energy, advancing clean coal technology, diminishing and decreasing reliance on coal targets and achieving sustainable development of energy.

Republic ofChina (2001-2005)	URL:http://www.nrel.gov/docs/fy04osti/35786.pdf.

The policies related to specific industries such as agriculture, transportation, building and residential industries are excluded. *Source*: Website of International Energy Agency (IEA). <http://www.iea.org/policiesandmeasures/renewableenergy/?country=China>.

Table A10. Policies related to the development of non-fossil energy for power generation.

Policy Title	Year	Policy Status	Policy targets
Renewable Electricity Quota and Assessment Method (Draft for Opinions)	2018	Planned	The mandatory provincial-level quotas of renewable electricity over total electricity and specific non-hydropower renewable electricity quotas are being established for the year 2018 and year 2020. URL: http://zfxxgk.nea.gov.cn/auto87/201803/t20180323_3131.htm
Opinion on Mechanism of Support for Local Populations in respect to Hydropower Projects Development	2018	In Force	Form and implement a comprehensive framework of policies and benefits supporting local populations and migrated populations relocated in consequence of the hydropower project development. Those policies and mechanism should be adopted by 2020. URL: http://www.ndrc.gov.cn/gzdt/201803/t20180330881009.html
Notice on Provisional Management Measures for Distributed Wind Power Project Development and Construction for all provinces	2018	In Force	The Notice provides regulations of Technical requirements, Grid connection model, Land Use and Marketization for the construction and development of the onshore wind projects. URL:http://zfxxgk.nea.gov.cn/auto87/201804/t20180416_3150.htm
Action Plan for the Development of Smart Photovoltaic Industry	2018	In Force	Facilitate the development of Chinese solar PV manufacturing industry in order to implement and benefit from intelligent automation and the newest new technologies available by 2020. URL:http://www.miit.gov.cn/n1146295/n1652858/n1652930/n3757021/c6140298/content.html
Renewable Energy Green Certificate and Trading Mechanism	2017	In Force	In order to ease government subsidies to wind and solar sectors, National Development and Reform Commission (NDRC) will begin issuing green certificates starting July 2017. This is a voluntary trading mechanism. According to the activeness of the voluntary trading market, a mandatory green certificate market is planned to be launched since 2018. URL:http://www.ndrc.gov.cn/zcfb/zcfbtz/201702/t20170203_837117.html
Guiding Opinion on Implementation of the China 13th Renewable Energy Development Five Year Plan (2016-2020)	2017	In Force	The Guiding Opinion gives a discretionary guidance on the construction scale, distribution layout and implementation roadmap of implementation of wind (110.41 GW), photovoltaic (PV) (86.5 GW), hydroelectric, and biomass (23.34 GW) power generation from 2017 to 2020. URL:http://zfxxgk.nea.gov.cn/auto87/201707/t20170728_2835.htm
Notice on Formulation	2017	In Force	The document stipulates that solar PV projects should be

of the 13th Five Year Plan for Solar Power Poverty Alleviation			constructed, in particular, in villages that historically struggle with poverty. The guidelines of capacities and project size are provided. Meanwhile, the programs to support the PV projects are also regulated. URL:http://zfxxgk.nea.gov.cn/auto87/201708/t20170808_2839.htm
China 13th Hydropower Development Five Year Plan (2016-2020)	2016	In Force	The targets for installed capacity and power capacity of hydropower in 2020 are regulated. URL:http://zfxxgk.nea.gov.cn/auto87/201611/t20161130_2324.htm
China 13th Wind Energy Development Five Year Plan (2016-2020)	2016	In Force	The cumulative installed capacity and new installed capacity of wind power in different regions are regulated. URL: http://www.nea.gov.cn/2016-11/29/c_135867633.htm
Notice on solar PV deployment management and introduction of competitive bidding	2016	In Force	To promote PV industry development sustainability, National Energy Administration (NEA) introduced new mechanism of PV scale management and competitive quota. The bidder with lower price and other indicators will be awarded the right to build PV power plant. URL:http://zfxxgk.nea.gov.cn/auto87/201601/t20160114_2096.htm
China 13th Geothermal Energy Development Five Year Plan (2016-2020)	2016	In Force	The targets for land use, newly installed capacity and annual utilization volume of geothermal power by 2020 are set. URL:http://www.sdpc.gov.cn/zcfb/zcfbtz/201702/t20170204_837203.html
China 13th Solar Energy Development Five Year Plan (2016-2020)	2016	In Force	The targets for Solar PV and Concentrating Solar Power in 2020 are set. URL: http://zfxxgk.nea.gov.cn/auto87/201612/t20161216_2358.htm
China 13th Energy Technology Innovation Five Year Plan (2016-2020)	2016	In Force	China aims to achieve advancements in renewable, fossil fuel and nuclear technologies as well as mini-grid, super-grids and smart-grids in order to increase country's competitiveness in the energy sector internationally. URL:http://zfxxgk.nea.gov.cn/auto83/201701/t20170113_2490.htm
China 13th Ocean Energy Development Five Year Plan (2016-2020)	2016	In Force	The target for cumulative installed ocean capacity are set by 2020. The technology development priority, strengthen in R&D and other measures should be implemented by 2020. URL:http://www.soa.gov.cn/zwgk/zcgh/kxcg/201701/t20170112_54473.html
Notice on the Administrative Measures for the Development and Construction of Offshore Wind Power	2016	In Force	The Notice regulate every aspect of offshore wind project development starting from planning to project operation. The Notice also regulates development of offshore wind projects close to islands. URL:http://zfxxgk.nea.gov.cn/auto87/201701/W020170104587578268083.doc
Guidelines on promoting development of small hydropower	2016	In Force	By 2020, create standards of small hydropower management, promote the system of incentives about small hydropower installations, and create a number of small hydropower

projects in China			demonstration projects. By 2030, develop and strengthen small hydropower industry. URL:http://shp.mwr.gov.cn/snzygl/201612/t20161223_776760.html
China 13th Renewable Energy Development Five Year Plan (2016-2020)	2016	In Force	Increase share of non-fossil energy in total primary energy consumption to 15% by 2020 and to 20% by 2030. Targets for installed renewable power capacity by 2020 are also set. The renewable energy technology innovation should be promoted. URL: http://www.nea.gov.cn/2016-12/19/c_135916140.htm
Feed-in tariff for CSP	2016	In Force	In order to support deployment of CSP and CSP industry development, NDRC adopted feed-in tariff (FIT) system for the technology. The FIT level for CSP is 1.15Yuan/kWh. The support is granted for period of 20 years. URL:http://zfxxgk.ndrc.gov.cn/PublicItemView.aspx?ItemID={3599e717-247f-43b2-b398-d7da858b7463}
China Energy Technology Innovation Action Plan 2016-2030	2016	In Force	The document is in line with goals included in 13th Energy Technology Innovation Five Year Plan (2016-2020) and leads the country beyond that timeline until 2030. China’s goal is to significantly enhance innovation in energy technologies, equipment, components and materials used in energy projects and to reduce China’s dependence on foreign suppliers for renewable energy projects (wind, solar, bioenergy, geothermal and ocean energy). URL:http://www.gov.cn/xinwen/2016-06/01/content_5078628.htm
China 13th Electricity Development Five Year Plan (2016-2020)	2016	In Force	The targets for installed capacity of hydropower, onshore wind, offshore wind, solar PV and bioenergy during 13th FYP are set. Non-fossil fuel cumulative electricity capacity to reach around 770 GW by 2020. URL:http://www.sdpc.gov.cn/zcfb/zcfbghwb/201612/P020161222570036010274.pdf
China 13th Bioenergy Development Five Year Plan (2016-2020)	2016	In Force	Targets for bioenergy generation capacity as well as the detailed technologies, such as direct combustion from traditional biomass, waste, biogas, large-scale biogas, solid biomass and bio-ethanol are set during 13th FYP. URL:http://www.ndrc.gov.cn/fzgggz/fzgh/ghwb/gjjgh/201708/t20170809_857320.html
Notice on increase of solar PV installations in 2015	2015	Ended	NEA issued a Notice that the amount of new solar PV capacity will be added in 2015 at level of 17.8 GW. The Notice was issued in order to stabilize the market and the target is split for 28 provinces. URL:http://zfxxgk.nea.gov.cn/auto87/201509/t20150928_1967.htm
Notice on construction of solar thermal power generation demonstration project	2015	Ended	NEA will organize a batch of solar thermal power projects to expand the scale of the solar thermal industry and cultivating system integrators. URL:http://zfxxgk.nea.gov.cn/auto87/201509/t20150930_1968.htm

Notice on pilot programs for locally consumed renewable energy power	2015	Ended	NDRC launched pilot projects supporting locally consumed renewable energy in Gansu province and Inner Mongolia. URL:http://www.gov.cn/xinwen/2015-10/20/content_2950300.htm
Guidance to improve electric power operation facilitating further development of clean energy	2015	In Force	Usage of compensation mechanism for clean energy fully in order to assure deployment. Strengthening electric power demand side management through the peak shift to create favorable conditions for clean energy. URL: http://www.nea.gov.cn/2015-04/09/c_134136821.htm
Guideline on promoting advanced photovoltaic technology application and industrial upgrading	2015	Ended	NEA will implement the "leader" projects to promote the advanced PV technology application and industrial upgrading, enhance the PV products and engineering quality management, improve the PV products market access standard, as well as guide the PV technology progress and industrial upgrading. URL:http://zfxxgk.nea.gov.cn/auto87/201506/t20150608_1935.htm
Guidance about promoting new energy micro grid demonstration project	2015	In Force	Explore technology and operation management of micro grids; Put requirements on construction of micro grids; Create accurate planning and provide good quality construction and management of micro grids. URL:http://zfxxgk.nea.gov.cn/auto87/201507/t20150722_1949.htm
Interim management measures on renewable energy development funds	2015	In Force	This regulation is to promote renewable energy development and utilization, optimize energy structure, and ensure energy security in accordance with the relevant laws and regulations. URL:http://jjs.mof.gov.cn/zhengwuxinxi/zhengcefagui/201504/t20150427_1223373.html
Guideline on preparation of Renewable Energy Development Plan of provinces in 13th Five Year Plan	2015	Ended	To apply scientific reasoning for deployment of all renewable energy technologies and reaching renewable goals in five year period of the 13th Plan. Other measures for renewable energy development are also provided. URL: http://fjb.nea.gov.cn/news_view.aspx?id=24636
Notice regulating the standardization of the wind power equipment and generators quality	2014	In Force	The Notice puts an obligation on provinces to strengthen the quality of wind power equipment and generators through standardize quality checking processes for wind plant equipment and windmills commissioning. The Notice underlines the importance of transparent and clear processes in wind equipment procurement. URL:http://zfxxgk.nea.gov.cn/auto87/201409/t20140925_1841.htm
Notice on further promotion of the distributes solar PV systems	2014	In Force	The Notice is directed to the provinces obliging them to strengthen further deployment of small-scale solar PV. URL: http://zfxxgk.nea.gov.cn/auto87/201409/t20140904_1837.htm
Notice on promotion of solar PV deployment	2014	In Force	The Notice puts many requirements on provinces in regards to solar PV deployment.

and on improvement of their operation management			URL:http://zfxxgk.nea.gov.cn/auto87/201410/t20141013_1847.htm
Notice regulating the standardization of investment and development of PV plants	2014	In Force	The Notice provides a guideline for investment and development of the PV plants in order to increase the efficiency, quality and transparency. URL:http://zfxxgk.nea.gov.cn/auto87/201410/t20141029_1857.htm
Notice promoting the construction of distributed solar PV demonstration projects	2014	In Force	The Notice increases a number of demonstration zones for distributed solar PV projects. The Notice encourages the demonstration areas to follow a specialized and innovative model of PV projects. URL:http://zfxxgk.nea.gov.cn/auto87/201412/t20141224_1874.htm
Notice of the State Development and Reform Commission on offshore wind power electricity price policy	2014	In Force	The way of determining the feed-in tariff of wind power is identified. URL:http://www.sdpc.gov.cn/gzdt/201406/t20140619_615709.html
Notice on issues concerning State Grid Corporation of China to buy distributed PV power generation projects' electricity products invoice etc.	2014	In Force	The notice regulate the invoice issues of buying electricity from distributed PV project power products. URL:http://www.chinatax.gov.cn/n2226/n2271/n2272/c735530/content.html
Notice on planning the exploitation and utilization of geothermal energy for power and heating	2014	In Force	The Notice provides a general guidance on short and long term development of the geothermal power in China. URL:http://zfxxgk.nea.gov.cn/auto87/201407/t20140710_1819.htm
NEA Notice on new solar PV capacity to be added in 2014	2014	In Force	From 2014 onwards the scale of newly added solar PV capacities will be under control and guidance of the NEA. The targets for new solar capacity in 2014 are set. URL: http://zfxxgk.nea.gov.cn/auto87/201402/t20140212_1763.htm
Interim Measures for the new power access network supervision	2014	In Force	This measure is to regulate the grid-connection of newly-constructed power grid and guarantee that the newly-constructed power grid is fairly connect to the grid. URL: http://www.nea.gov.cn/2014-03/14/c_133186385.htm
Notice of VAT policy of large-scale hydropower enterprise	2014	In Force	This Notice is to support hydropower development, and formulate tax policy for large scale hydropower corporation. URL:http://www.gov.cn/xinwen/2014-03/12/content_2636943.htm
Notice on strengthening management of biomass power stations	2014	In Force	The Notice encourages the development of biomass power stations in provinces, stresses out the importance of improving the efficiency of plants and forbids the usage of forest and agriculture biomass residue for co-firing with fossil fuels. URL: http://www.sdpc.gov.cn/gzdt/201412/t20141229_65837

			8.html
China offshore wind power development plan (2014-2016)	2014	In Force	The Plan aims to construct 44 offshore wind projects with total capacity of 10.53 GW until the end of 2016. URL: http://news.bjx.com.cn/html/20141212/572679.shtml
Notice on preparing the 13th Five Year Plan on solar PV development (2016-2020)	2014	Ended	The NEA requests provincial energy departments to conduct research projects and prepare the deployment of solar PV for the period of 2016-2020 that will ultimately feed into the 13th Five Year Plan of China. URL: http://guangfu.bjx.com.cn/news/20141224/576124.shtml
Notice on grid connection for solar PV projects in 2014	2014	In Force	The Notice requests provinces to improve access and expansion of grid in coordination with installation of new solar PV generators. The Notice calls for improvement of management and planning of solar PV projects. URL:http://www.cec.org.cn/zhengcefagui/2014-12-24/131854.html
Feed-in tariff support for solar PV	2013	In Force	The feed-in tariff and subsidy for distributed solar PV are regulated. URL:http://www.ndrc.gov.cn/zcfb/zcfbtz/201612/t20161228_833049.html
Adjustment of surcharge of renewable electricity generation	2013	In Force	From 25 September 2013, the surcharge for the renewable electricity generation and upgraded subside for coal-fired plants with technology lowering emissions of nitrogen oxide are increased. URL: http://www.nea.gov.cn/2014-09/29/c_133682226.htm
Notice on the policy of PV electricity VAT	2013	In Force	The value-added tax policy for photovoltaic power generation is developed to encourage the use of solar power. URL:http://szs.mof.gov.cn/zhengwuxinxi/zhengcefabu/201309/t20130929_994642.html
Notice on promotion of PV industry by exert the price leverage effect	2013	In Force	In order to promote the development and utilization of renewables, other electricity users should pay renewable energy tariff except for residents living and agricultural production since September 25, 2013. URL:http://zfxxgk.ndrc.gov.cn/PublicItemView.aspx?ItemID={8b110215-2e8b-4fb6-bb82-bedd0651794a}
Code of practice of the PV manufacturing	2013	In Force	This regulation is to regulate the establishment of the production, operation, project construction, production scale, technology and resource utilization of PV manufacturing industry. URL:http://www.gov.cn/zwgk/2013-09/17/content_2490100.htm
Interim procedures of management of the code of practice of PV manufacturing	2013	In Force	This procedure is to strengthen the management, speed up the transformation and upgrade the PV manufacturing industry. Provide information on the application, auditing, supervision and management of PV manufacturing industry. URL:http://www.miit.gov.cn/n11293472/n11293832/n11293907/n11368223/15659809.html
Distributed photovoltaic power generation service guide of China	2013	In Force	This guide is to strengthen services for distributed solar power projects and promote orderly development of PV industry. URL:

Southern Power Grid Company Limited (Interim)			https://wenku.baidu.com/view/4379d45cccbff121dc368352
The state council's comments on promote the development of the PV industry	2013	In Force	This file is to deal with the current problems the PV industry is facing, and further regulate and promote the sustainable development of this industry. A target for installed capacity of PV power during 2013-2015 is set. URL: http://www.gov.cn/zwgk/2013-07/15/content_2447814.htm
Notice on the related issues of the application of subsidies based on electric quantity of distributed PV power grid	2013	In Force	This notice gives the detail information of subsidies for distributed PV power generation, such as the subsidy standard, provision of electricity and the way to give the subsidies. URL: http://jjs.mof.gov.cn/zhengwuxinxi/tongzhigonggao/201307/t20130731_971420.html
Comments on the promotion of the development and utilization of geothermal energy	2013	In Force	The target for installed capacity of geothermal power by 2015 is set. The targets for utilization of geothermal energy capacity in 2015 and 2020 are also set. URL:http://zfxxgk.nea.gov.cn/auto87/201302/t20130207_1581.htm
Notice on the improvement of the grid connection and assimilation of wind electric power generation in 2013	2013	Ended	The NEA has issued several comments to improve the wind power utilization rate, such as the utilization of wind power electricity and the research of the utilization methods for the regions that have abundant resources. URL: http://www.gov.cn/zwgk/2013-03/19/content_2357397.htm
The Notice on Integrating and Accommodating Wind Power 2013	2013	In Force	The Notice is used to identify the major problems of wind power development, improve the wind accommodation and utilization rate, analyze the reason of curtailment and get rid of the barriers. URL:http://www.gov.cn/zwgk/2013-03/19/content_2357397.htm
Comments on support of PV power financial services	2013	In Force	This comment is to maximize leverage to effectively stimulate distributed PV investments. The Chinese government provide many ways for financial support of PV power generation. URL: http://www.nea.gov.cn/2014-09/04/c_133620586.htm
The Interim Measures for the management of photovoltaic power plant project	2013	In Force	State Council authorities can determine the scale and layout of PV power plant construction at the national level, and annual development scales at the province level. The project record management, such as location planning, resource evaluation, construction condition argumentation, and market demand analysis, is required before the construction of new PV power plants. URL: http://www.nea.gov.cn/2014-09/04/c_133620583.htm
The Notice on the Establishment of Demonstration Areas for Large-Scale distributed solar PV Power Generation	2012	In Force	The generation capacities of solar should fully meet power demand of the targeted areas. Smart-grid technologies should be encouraged. The Notice implements standards for subsidy creation of self-generation systems and net metering mechanism. Installed generation capacity per province is also regulated during 2012-2017.

			URL:http://www.gov.cn/zwgk/2012-09/28/content_2235051.htm
China Energy White Paper 2012	2012	In Force	The targets for the share of non-fossil fuels in primary energy consumption and installed generation capacity of non-fossil fuels by 2015 are set. URL:http://www.gov.cn/english/official/2012-10/24/content_2250497.htm
The Notice on New Energy Demonstration City and Industrial Park	2012	In Force	The ratio of renewable energy consumption and the evaluation indicators for PV, wind, geothermal energy and others are regulated. URL:http://www.cec.org.cn/zhengcefagui/2012-08-15/89229.html
Notice on feed-in tariff for co-firing generators burning coal and household waste	2012	In Force	The Notice regulates the electricity tariff (feed-in tariff) for generators producing electricity by household waste. URL: http://www.gov.cn/zwgk/2012-04/10/content_2109921.htm
Solar Power Technology Development 12th Five Year Special Plan	2012	In Force	The goal of utilization efficiency improvement is set, including crystalline silicon cells, silicon thin-film cell, and cadmium telluride, and copper indium gallium selenide thin-film batteries. URL:http://www.most.gov.cn/fggw/zfwj/zfwj2012/201204/t20120424_93887.htm
Wind Power Technology Development 12th Five Year Special Planning	2012	In Force	The target of offshore wind prototypes by 2015 is set. Over the next five years, industry will be also focused on development of various offshore wind systems. URL:http://www.gov.cn/zwgk/2012-04/24/content_2121636.htm
The Renewable Energy Tariff Surcharge Grant Funds Management Approach	2012	In Force	The standard of subsidies for renewable energy power generation is established. URL:http://jjs.mof.gov.cn/zhengwuxinxi/zhengcefagui/201203/t20120329_638930.html
2012 Renewable Energy Electricity feed-in tariff	2012	In Force	It lists over 200 renewable energy electricity projects allocated in ten provinces which will get subsidies in 2012. URL:http://www.nea.gov.cn/2012-06/27/c_131679488.htm
12th Five Year Plan for National Strategic Emerging Industries	2012	In Force	The plan sets a goal to further develop new energy technologies, such as nuclear power, wind, solar PV, geothermal, biomass electricity generation and methane gas in order to actively advance the industrialization of renewable resource technology. URL:http://www.gov.cn/zwgk/2012-07/20/content_2187770.htm
Interim Measures on Renewable energy development fund Imposition and Management	2012	In Force	Policy outlines the funding measures, management, supervision and inspection mechanism of Renewable Energy Development Fund. Scheme will continue to support scientific and technological research. URL: http://www.nea.gov.cn/2011-12/20/c_131316289.htm

Solar Industry 12th Five Year Development Planning	2012	Ended	This plan aims to reduce the cost of solar power and increase production of solar panels by 2015 and 2020. Additionally, more efforts will be made to the production technology for BIPV and the conversion efficiency of monocrystalline in the coming years. URL:http://www.miit.gov.cn/n11293472/n11293832/n11293907/n11368223/14473431.html
The Twelfth Five-Year Plan for Renewable Energy	2012	In Force	The targets by the end of 2015 for total consumption of renewable energy and different types of renewable energy are set. URL: http://www.nea.gov.cn/2012-08/08/c_131767651.htm
Solar PV feed-in tariff	2011	In Force	The standards of feed-in tariff for various solar PV projects are regulated. URL: http://www.nea.gov.cn/2011-08/01/c_131097437.htm
The Twelfth Five-Year Plan for Renewable Energy of Beijing	2011	In Force	The 12th FYP on Renewable Energy of Beijing outlines targets on renewable energy, and how they fit into Beijing's economic development. URL:http://www.sdpc.gov.cn/dffgwdt/t20111229_453384.htm
The 12th Five-Year Plan for Economic and Social Development of the People's Republic of China (2011-2015)	2011	Superseded	The Plan includes some energy targets, such as the share of non-fossil fuel resources, energy intensity and carbon intensity by 2015. The plan also incorporates specific deployment targets for renewable energies. URL:http://www.moa.gov.cn/fwllm/jjps/201103/t2011031719 49003.htm
Import duty removal on wind and hydro technological equipment	2010	Ended	This decision is to remove import duties and value added taxes on key technological equipment. The Catalogue on Key Technological Equipment includes products used to generate wind and hydro power. URL:http://"http://www.cnnsr.com.cn/cssw/swhtml/20151217080008182942.html
Building Integrate Solar PV Program	2010	In Force	The 2009 Building Integrated Solar PV Program provides upfront subsidies for grid-connected rooftop and Building Integrated Solar PV (BIPV) systems. URL: http://en.ndrc.gov.cn/
2010 Biomass electricity Feed-in tariff	2010	In Force	In 2010, the NDRC announced a new national feed-in tariff for biomass power and the biomass installed capacity target by 2020. URL: http://en.ndrc.gov.cn/
Interim Feed-in Tariff for Four Ningxia Solar Projects	2010	Superseded	The NDRC set up a special feed-in tariff for four PV power plants in the Ningxia province. The projects, of a total capacity of 40 MW, are being developed by the China Energy Conservation Investment Corporation, the Huadian Group Corporation and Ningxia Electric Power. URL:http://www.ndrc.gov.cn/zfdj/jggg/dian/t20100409_339709.htm
Market entry standards for wind equipment manufacturing industry:	2010	In Force	This regulation is used to improve the efficiency and competitiveness of the local wind equipment manufacturing market.

			URL: http://www.en.ndrc.gov.cn
Golden Sun Program	2009	Ended	The 2009 Golden Sun program provides subsidies to grid connected and off-grid solar PV power generation projects and calls for 500 MW of installed PV capacity by 2012. Subsidy schemes have been designed both at the national and provincial levels and apply to 2011. URL: http://en.ndrc.gov.cn/
Feed-in tariff for onshore and offshore wind	2009	In Force	The price setting is divided in four categories according to the wind resources of the region, the larger the wind resources the lower the financial support. URL:http://www.ndrc.gov.cn/zcfb/zcfbtz/201612/t20161228_833049.html
Notice on the removal of local content requirement in wind power projects equipment procurement	2009	In Force	The 2005 Notice of the NDRC on the Management of Wind Power Construction imposed a local content requirement on wind plants. All newly installed wind power turbines had to purchase 70% of their components domestically to receive building approval. URL:http://www.sdpc.gov.cn/zcfb/zcfbtz/2009tz/t20101014_374927.htm
Offshore Wind development plan	2009	In Force	This plan requires all coastal regions to establish their own offshore Wind Development Roadmap to 2020. The Development Plan also establishes the official baseline for offshore projects. URL: http://en.ndrc.gov.cn/
Renewable Energy Law amendments	2009	In Force	In the course of 2009, the 2006 Renewable Energy Law experienced some amendments. URL: http://www.gov.cn/english/links/statecouncil.html
International Science and Technology Cooperation Program for New and Renewable Energy	2008	In Force	The program aims to introduce cutting-edge technologies in the national market, attract overseas scientists and develop exchange programs with international research centers. Specific attention is devoted to research in the fields of solar power generation and solar power building structures, biomass gasification and power generation, and large high-efficiency wind turbines for onshore and offshore projects. URL: http://ie.china-embassy.org/eng/ScienceTech/iccst/P020080422041207665736.pdf
Medium and Long Term Development Plan for Renewable Energy	2007	Superseded	The Plan establishes targets for the development of various renewable energies (hydropower, wind power, biomass, solar power and biofuels) up to 2020, and calls for the percentage of renewable energy to rise to 10% of total energy consumption by 2010 and 15% by 2020. URL:http://www.martinot.info/China_RE_Plan_to_2020_Sep-2007.pdf
US China MOU on Biomass Development	2007	In Force	The United States and China signed a Memorandum of Understanding (MOU) in 2007 to promote further research and utilization of biomass. The MOU outlines a variety of tasks for cooperative efforts between the two countries, focusing on the exchange of scientific, technical and policy information on biomass production. URL: http://www.eere.energy.gov/pdfs/chinamou.pdf

Special Fund for the Industrialization of Wind Power Equipment	2007	In Force	The Ministry of Finance creats the Special Fund for the Industrialization of Wind Power Equipment. The institution allocates funding to wind projects assessment and evaluation studies, related technology research and development, as well as the construction of pilot demonstration projects. The fund also supports the production of new wind turbines equipment. URL: http://www.mof.gov.cn/
Renewable Energy Law of the People's Republic of China	2006	In Force	The Renewable Energy Law is a framework policy which lays out the general conditions for renewable energy to become a more important energy source in China. URL: http://www.creia.net
The 11th Five-Year Plan for Economic and Social Development of The People's Republic of China (2006-2010)	2006	Superseded	It contains a number of measures designed to increase the share of renewable energy in China's energy portfolio by 2010, such as wind farms, grid-connected wind and biomass. URL:http://en.ndrc.gov.cn/newsrelease/200603/t20060323_63813.html
The 10th Five-Year Plan for Economic and Social Development of the People's Republic of China (2001-2005)	2001	Ended	The principal objectives of the plan include the sufficient utilization of clean energies (e.g., natural gas, hydropower and nuclear power), the promotion of new energy and renewable energy (e.g., solar PV and wind), the improvement in clean coal technology, less dependent on coal, and the achievement of energy sustainable development. URL:http://china.org.cn/e-15/index.htm

Source: Website of International Energy Agency (IEA).
<http://www.iea.org/policiesandmeasures/renewableenergy/?country=China>.

Website of National Development and Reform Commission. < http://www.ndrc.gov.cn/ >.

Website of Ministry of Industry and Information Technology of the People's Republic of China.

<http://www.miit.gov.cn/>.

Table A11. Key elements of the "Made in China 2025" initiative.

Policy item	Policy targets	Remarks
Performance targets	•Improve industrial energy intensity by 18% in 2020 and 34% in 2025, relative to 2015.	Energy efficiency improvement
	•Improve industrial CO_2 intensity by 22% in 2020 and 40% in 2025, relative to 2015.	Carbon intensity reduction
	• Increase manufacturing value added by 2% in 2020 and 4% in 2025, relative to 2015.	Increase of manufacturing output
	• Improve industrial value-added growth to 9.9% by 2025, compared with 5.9% in 2015.	Increase of industrial output
	• Improve reuse of solid industrial waste from 65% in 2015 to 79% by 2025.	Reuse of industrial solid
	• Increase rate of use of process control systems in key production processes from 33% in 2015 to 64% in 2025.	Improve equipment utilization
	• Increase internal research and development cost as a	Increase R&D

	percentage of operating revenue of manufacturing firms from 0.95% in 2015 to 1.68% in 2025.	expenditure
	• 7.5% growth of average manufacturing labor productivity by 2020, remaining at 7.5% until 2025.	Increase labor productivity
Industrial development targets	• Increase the share of essential spare parts and key materials produced domestically to 40% by 2020 and 70% by 2025.	Self-sufficiency
	• Build 15 industrial technology research bases by 2020 and aim to build 40 by 2025.	Technology improvement
	• Develop 1,000 green demonstration factories and 100 green demonstration industrial parks by 2020.	General targets
Policy and regulatory changes	• Upgrade manufacturing, in which 90% of manufacturing quality standards will meet international requirements by 2020 in key areas, compared with 70% today.	Improve manufacturing quality
	• "100-1,000-10,000" energy conservation program to regulate the top-100 energy consuming enterprises by the national government; the top-1,000 by provincial governments; and the top-10,000 by local governments.	Energy conservation

Source: IEA, 2017. World Energy Outlook 2017. <https://www.iea.org/weo2017/>.

Website of "Made in China 2025". <http://www.miit.gov.cn/n973401/n1234620/index.html>.

Table A12. Selected industry-related targets up to 2020.

Industry-related policies from 2001 to 2015		
Policy item	Policy targets	Remarks
Industry-wide targets	• Promote the industrialization and local manufacturing of efficient and clean energy technologies such as boilers, motors, regenerative combustion technology, new energy vehicles, and semi-conductor lighting.	Technology improvement
	• Top 1000 Industrial Energy Conservation Program.	Energy conservation
	• Top 10000 Enterprises Energy Conservation and Low Carbon Action.	Energy conservation
Energy-intensive industries-2004	• A differential energy pricing scheme for high energy-consuming industries and products was established.	Energy conservation
	• The expansion of high-pollution and energy-intensive industries are heavily restricted, alongside the phase-out of obsolete technologies and excess capacity.	Industrial structure adjustment
Sub-sectors-2006	• Equipment renovation and the implementation of process optimization and management measures. Targeting at the metallurgical industry, petrochemical industry and chemical industry.	Technology improvement
Industry-related policies in China's 13th Five-Year Plan and Industrial Green Development Plan (2016-2020)		
Policy item	Policy targets	Remarks
Industry-wide targets	• Implement further air pollution control technologies in industrial boilers, and steel and cement making process equipment. Clean and efficient use of coal.	Technology improvement

	• Reconstruction of high-energy general-purpose equipment: By 2020, the average operating efficiency of electric motors and internal combustion engine systems will increase by 5%, and the proportion of efficient distribution transformers in the network will increase by 20%.	Energy efficiency improvement
	• Focus on accelerating key branches including: high value-added equipment, integrated circuits, biotechnology, cloud computing, new energy technology and advanced materials.	Industrial structure adjustment
	• Improvement of energy efficiency and the level of cleaner production.	Energy efficiency improvement
	• Development of the green manufacturing industry and establishment of the green manufacturing system.	Environmentally approach
	• 80% utilization rate of low-grade residual heat and residual pressure.	Technology improvement
	• 20% decrease in emission intensity of major pollutants in key industries.	Reduction of pollutants
	• 28% cumulative decrease in energy intensity of enterprises above designated size.	Energy efficiency improvement
	• 3% increase in the proportion of green low-carbon energy consumption in total industrial energy consumption.	Energy structure adjustment
	• The industry output value of green manufacturing industry increase from 5.3 trillion yuan in 2015 to 10 trillion yuan in 2020.	Industrial structure adjustment
Energy-intensive industries	• Six high-energy-consuming industries accounted for industrial added value decrease from 27.8% to 25%.	Industrial structure adjustment
Cement and other building materials plan	• 10% clinker capacity reduction.	Product structure adjustment
	• 6% improvement in thermal energy intensity of clinker production.	Energy efficiency improvement
	• 50% decrease in specific SO_2 emissions from plate glass.	Reduction of pollutants
	• 30% decrease in annual NO_X emissions from ceramics.	Reduction of pollutants
Iron and steel plan	• At least 10% decrease in energy consumption.	Energy conservation
	• Increase utilization rate to at least 90%.	Efficiency improvement
	• 100-150 Mt capacity reduction for crude steel.	Product structure adjustment
	• Improve energy intensity to less than 560 kgce/t steel.	Energy efficiency improvement
	• At least 15% reduction in pollutant emissions.	Reduction of pollutant emissions
Petrochemical and chemical plan	• 8% annual growth in value added.	Increase of industrial output
	• 18% decrease in energy intensity	Energy efficiency improvement
	• 18% decrease in CO_2 intensity per unit of value added.	Carbon intensity reduction

Non-ferrous metals plan	• 18% decrease in energy intensity per unit of value added for enterprises above threshold income level.	Energy efficiency improvement
	• 15% decrease in total annual SO_2 emissions.	Reduction of pollutants
Textiles plan	• 6-7% annual increase in value added, for enterprises above threshold income level.	Increase of industrial output
	• 18% decrease in energy intensity.	Energy efficiency improvement
Light industry plan	• Shift light industry from coastal region to Central and Western regions.	Industry relocation
	• Construct modern industrial clusters to encourage technology development, energy savings and emissions reductions.	Technology improvement

Source: IEA, 2017. World Energy Outlook 2017. <https://www.iea.org/weo2017/>.

Industrial Green Development Plan (2016-2020), <http://www.miit.gov.cn/n1146295/n1652858/n1652930/n3757016/c5143553/content.html>.

National Development and Reform Commission (NDRC), 2004. The Trial Implementation of Differential Pricing Policy in 6 High Energy-intensive Industries (2004-2012). <http://www.sciencedirect.com/science/article/pii/S0301421512001668>.

National Development and Reform Commission (NDRC), 2006. Top 1000 Industrial Energy Conservation Program. <http://www.ndrc.gov.cn/rdzt/jsjyxsh/200604/t20060413_66114.html>.

National Development and Reform Commission (NDRC), 2013. Plan for accelerating the development of energy conservation and environmental protection related industries. <http://www.gov.cn/zwgk/2013-08/11/content_2464241.htm>.

National Development and Reform Commission (NDRC), 2014. National Energy Strategic Action Plan for Energy Development. (2014-2020). <http://www.gov.cn/zhengce/content/2014-11/19/content_9222.htm>.

Table A13. The share of IVA (industrial value added) in GDP and future GDP in China.

Year	Share of IVA (%)	GDP (Billion yuan/yr)
2006	47.56	18015.95
2007	46.86	20574.21
2008	46.93	22569.91
2009	45.88	24691.48
2010	46.40	27308.78
2011	46.40	29903.11
2012	45.27	32265.46
2013	44.01	34782.16
2014	43.10	37321.26
2015	40.93	39896.43
2016	39.88	42569.49
2017	40.56	45464.21
2018	39.98	48373.92
2019	39.42	51421.48
2020	38.86	54609.61

2021	38.31	57776.97
2022	37.76	61128.03
2023	37.23	64673.46
2024	36.70	68424.52
2025	36.18	72393.14

The shares of IVA in GDP from 2006 to 2017 are historical data. The shares of IVA from 2018 to 2025 are calculated based on its average change rate over the past twelve years. GDP from 2006 to 2017 is historical data. GDP from 2018 to 2025 is calculated based on the growth rate forecast by World Bank <http://www.worldbank.org/en/publication/global-economic-prospects>. The data sets here are all 2000 constant price.

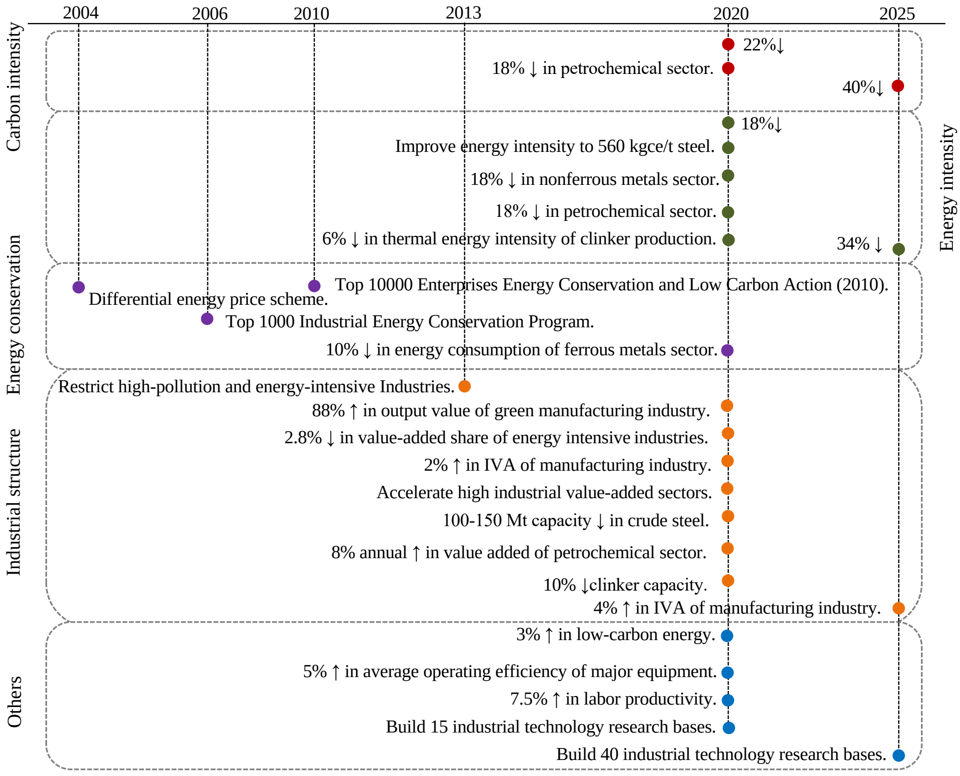

Fig. A2. Timeline of major targets for carbon-related indicators in industrial sector. The policies in lines 2020 and 2025 are on the basis of 2015.

References

[1] Liu LC, Fan Y, Wu G, Wei YM. Using LMDI method to analyzed the change of China's industrial CO_2 emissions from final fuel use: An empirical analysis. Energy Policy 2007; 35: 5892-5900.

[2] Zhao M, Tan LR, Zhang WG, Ji MH, Liu YA, Yu LZ. Decomposing the influencing factors of industrial carbon emissions in Shanghai using the LMDI method. Energy 2010; 35: 2505-2510.

[3] Shao S, Yang LL, Yu MB, Yu ML. Estimation, characteristics, and determinants of energy-related industrial CO_2 emissions in Shanghai (China), 1994-2009. Energy Policy 2011; 39: 6476-6494.

[4] Sun WQ, Cai JJ, Mao HJ, Guan DJ. Change in Carbon Dioxide (CO_2) Emissions From Energy Use in China's Iron and Steel Industry. Journal of Iron and Steel Research, International 2011; 18: 31-36.

[5] Yang J, Chen B. Using LMDI method to analyze the change of industrial CO_2 emission from energy use in Chongqing. Frontiers of Earth Science 2011; 5: 103-109.

[6] Ren SG, Hu Z. Effects of decoupling of carbon dioxide emission by Chinese nonferrous metals industry. Energy Policy 2012; 43: 407-414.

[7] Ren SG, Fu X, Chen XH. Regional variation of energy-related industrial CO_2 emissions mitigation in China. China Economic Review 2012; 23: 1134-1145.

[8] Wang ZH, Zhang B, Yin JH. Determinants of the increased CO_2 emission and adaption strategy in Chinese energy-intensive industry. Natural Hazards 2012; 62(1): 17-30.

[9] Chen L, Yang ZF, Chen B. Decomposition Analysis of Energy-Related Industrial CO_2 Emissions in China. Energies 2013; 6: 2319-2337.

[10] Wang ZH, Zhang B, Yin JH. Determinants of the increased CO_2 emission and adaption strategy in Chinese energy-intensive industry. Natural Hazards 2012; 62: 17-30.

[11] Zhao XL, Ma Q, Yang R. Factors influencing CO_2 emissions in China's power industry: Co-integration analysis. Energy Policy 2013; 57: 89-98.

[12] Lin BQ, Moubarak M, Ouyang XL. Carbon dioxide emissions and growth of the manufacturing sector: Evidence for China. Energy 2014; 76: 830-837.

[13] Ren SG, Yin HY, Chen XH. Using LMDI to analyze the decoupling of carbon dioxide emissions by China's manufacturing industry. Environmental Development 2014; 9: 61-75.

[14] Xu X, Zhao T, Liu N, Kang J. Changes of energy-related GHG emissions in China: An empirical analysis from sectoral perspective. Applied Energy 2014; 132: 298-307.

[15] Zhou G, Chung W, Zhang Y. Carbon dioxide emissions and energy efficiency analysis of China's regional thermal electricity generation. Journal of Cleaner Production 2014; 83: 173-184.

[16] Fan TJ, Luo RL, Xia HY, Li XP. Using LMDI method to analyze the influencing factors of carbon emissions in China's petrochemical industries. Natural Hazards 2015; 75: S319-S332.

[17] Liu N, Ma ZJ, Kang JD. Changes in carbon intensity in China's industrial sector: Decomposition and attribution analysis. Energy Policy 2015; 87: 28-38.

[18] Ouyang XL, Lin BQ. An analysis of the driving forces of energy-related carbon dioxide emissions in China's industrial sector. Renewable & Sustainable Energy Reviews 2015; 45: 838-849.

[19] Yu B, Li X, Qiao YB, Shi L. Low-carbon transition of iron and steel industry in China: Carbon intensity, economic growth and policy intervention. Journal of Environmental Sciences 2015; 28: 137-147.

[20] Deng MX, Li W, Hu Y. Decomposing Industrial Energy-Related CO_2 Emissions in Yunnan Province, China: Switching to Low-Carbon Economic Growth. Energies 2016; 9(1).

[21] Lin BQ, Long HY. Emissions reduction in China's chemical industry - Based on LMDI. Renewable & Sustainable Energy Reviews 2016; 53: 1348-1355.

[22] Lin BQ, Zhang ZH. Carbon emissions in China's cement industry: A sector and policy analysis. Renewable & Sustainable Energy Reviews 2016; 58: 1387-1394.

[23] Liu L, Wang SS, Wang K, Zhang RQ, Tang XY. LMDI decomposition analysis of industry carbon emissions in Henan Province, China: comparison between different 5-year plans. Natural Hazards 2016; 80: 997-1014.

[24] Shao S, Yang LL, Gan CH, Cao JH, Geng Y, Guan DB. Using an extended LMDI model to explore techno-economic drivers of energy-related industrial CO_2 emission changes: A case study for Shanghai (China). Renewable & Sustainable Energy Reviews 2016; 55: 516-536.

[25] Shi Y, Zhao T. A decomposition analysis of carbon dioxide emissions in the Chinese nonferrous metal industry. Mitigation and Adaptation Strategies for Global Change 2016; 21: 823-838.

[26] Wu R, Zhang J, Bao Y, Lai Q, Tong S, Song Y. Decomposing the Influencing Factors of Industrial Sector Carbon Dioxide Emissions in Inner Mongolia Based on the LMDI Method. Sustainability 2016; 8(7): 661.

[27] Wu RN, Zhang JQ, Bao YH, Tong SQ. Using a Geographically Weighted Regression Model to Explore the Influencing Factors of CO_2 Emissions from Energy Consumption in the Industrial Sector. Polish Journal of Environmental Studies 2016; 25: 2641-2651.

[28] Wu RN, Zhang JQ, Bao YH, Zhang F. Geographical Detector Model for Influencing Factors of Industrial Sector Carbon Dioxide Emissions in Inner Mongolia, China. Sustainability 2016; 8(2): 149.

[29] Xu B, Lin BQ. Reducing carbon dioxide emissions in China's manufacturing industry: a dynamic vector autoregression approach. Journal of Cleaner Production 2016; 131: 594-606.

[30] Xu B, Lin BQ. Reducing CO_2 emissions in China's manufacturing industry: Evidence from nonparametric additive regression models. Energy 2016; 101: 161-173.

[31] Xu B, Lin BQ. Regional differences in the CO_2 emissions of China's iron and steel industry: Regional heterogeneity. Energy Policy 2016; 88: 422-434.

[32] Xu B, Lin BQ. Assessing CO_2 emissions in China's iron and steel industry: A dynamic vector autoregression model. Applied Energy 2016; 161: 375-386.

[33] Xu SC, He ZX, Long RY, Chen H. Factors that influence carbon emissions due to energy consumption based on different stages and sectors in China. Journal of Cleaner Production 2016; 115: 139-148.

[34] Zhao XR, Zhang X, Shao S. Decoupling CO_2 emissions and industrial growth in China over 1993-2013: The role of investment. Energy Economics 2016; 60: 275-292.

[35] Jiang JJ, Ye B, Xie DJ, Li J, Miao LX, Yang P. Sector decomposition of China's national economic carbon emissions and its policy implication for national ETS development. Renewable & Sustainable Energy Reviews 2017; 75: 855-867.

[36] Lin BQ, Xu B. Which provinces should pay more attention to CO_2 emissions? Using the quantile regression to investigate China's manufacturing industry. Journal of Cleaner Production 2017; 164: 980-993.

[37] Liu N, Ma Z, Kang J. A regional analysis of carbon intensities of electricity generation in China. Energy Economics 2017; 67: 268-277.

[38] Wang J, Zhao T, Zhang XH. Changes in carbon intensity of China's energy-intensive industries: a combined decomposition and attribution analysis. Natural Hazards 2017; 88: 1655-1675.

[39] Wang M, Feng C. Understanding China's industrial CO_2 emissions: A comprehensive decomposition framework. Journal of Cleaner Production 2017; 166: 1335-1346.

[40] Wang Y, Zhang C, Lu AT, Li L, He YM, ToJo JJ, Zhu XD. A disaggregated analysis of the environmental Kuznets curve for industrial CO_2 emissions in China. Applied Energy 2017; 190: 172-180.

[41] Xu B, Lin BQ. Assessing CO_2 emissions in China's iron and steel industry: A nonparametric additive regression approach. Renewable & Sustainable Energy Reviews 2017; 72: 325-337.

[42] Xu B, Xu L, Xu RJ, Luo LQ. Geographical analysis of CO_2 emissions in China's manufacturing industry: A geographically weighted regression model. Journal of Cleaner Production 2017; 166: 628-640.

[43] Xu RJ, Lin BQ. Why are there large regional differences in CO_2 emissions? Evidence from China's manufacturing industry. Journal of Cleaner Production 2017; 140: 1330-1343.

[44] Xu RJ, Xu L, Xu B. Assessing CO_2 emissions in China's iron and steel industry: Evidence from quantile regression approach. Journal of Cleaner Production 2017; 152: 259-270.

[45] Xu XB, Yang GS, Tan Y, Zhuang QL, Tang XG, Zhao KY, Wang SR. Factors influencing industrial carbon emissions and strategies for carbon mitigation in the Yangtze River Delta of China. Journal of Cleaner Production 2017; 142: 3607-3616.

[46] Yan D, Lei YL, Li L. Driving Factor Analysis of Carbon Emissions in China's Power Sector for Low-Carbon Economy. Mathematical Problems in Engineering 2017; 4954217.

[47] Zhang CQ, Zhang M, Zhang N. CO_2 Emissions from the Power Industry in the China's Iteijing-Tianjin-Hebei Region: Decomposition and Policy Analysis. Polish Journal of Environmental Studies 2017; 26: 903-916.

[48] Zhang XL, Zhao Y, Sun Q, Wang CJ. Decomposition and Attribution Analysis of Industrial Carbon Intensity Changes in Xinjiang, China. Sustainability 2017; 9(3): 459.

[49] Zhao X, Zhang X, Li N, Shao S, Geng Y. Decoupling economic growth from carbon dioxide emissions in China: A sectoral factor decomposition analysis. Journal of Cleaner Production 2017; 142: 3500-3516.

[50] Zhou X, Zhang M, Zhou MH, Zhou M. A comparative study on decoupling relationship and influence factors between China's regional economic development and industrial energy-related carbon emissions. Journal of Cleaner Production 2017; 142: 783-800.

[51] Du G, Sun CW, Ouyang XL, Zhang C. A decomposition analysis of energy-related CO_2 emissions in Chinese six high-energy intensive industries. Journal of Cleaner Production 2018; 184: 1102-1112.

[52] Jia JS, Gong ZH, Xie DM, Chen JH, Chen CD. Analysis of drivers and policy implications of carbon dioxide emissions of industrial energy consumption in an underdeveloped city: The case of Nanchang, China. Journal of Cleaner Production 2018; 183: 843-857.

[53] Liu J, Zhang SH, Wagner F. Exploring the driving forces of energy consumption and environmental pollution in China's cement industry at the provincial level. Journal of Cleaner Production 2018; 184: 274-285.

[54] Li XZ, Liao H, Du YF, Wang C, Wang JW, Liu YA. Carbon dioxide emissions from the electricity sector in major countries: a decomposition analysis. Environmental Science and Pollution Research 2018; 25: 6814-6825.

[55] Lin BQ, Xu B. Growth of industrial CO_2 emissions in Shanghai city: Evidence from a dynamic vector autoregression analysis. Energy 2018; 151: 167-177.

[56] Peng X, Tao XM. Decomposition of carbon intensity in electricity production: Technological innovation and structural adjustment in China's power sector. Journal of Cleaner Production 2018; 172: 805-818.

[57] Wang J, Hu M, Rodrigues JFD. An empirical spatiotemporal decomposition analysis of carbon intensity in China's industrial sector. Journal of Cleaner Production 2018; 195: 133-144.

[58] Wang JF, He ST, Qiu Y, Liu N, Li YJ, Dong ZF. Investigating driving forces of aggregate carbon intensity of electricity generation in China. Energy Policy 2018; 113: 249-257.

[59] Wang QW, Hang Y, Su B, Zhou P. Contributions to sector-level carbon intensity change: An integrated decomposition analysis. Energy Economics 2018; 70: 12-25.

[60] Wen L, Yan F, Li Y. Analysis of Influencing Factors of CO_2 Emissions in China's Power Industry and Policy Implications. Polish Journal of Environmental Studies 2018; 27: 373-382.

[61] Yan Q, Wang Y, Baležentis T, Sun Y, Streimikiene D. Energy-Related CO_2 Emission in China’s Provincial Thermal Electricity Generation: Driving Factors and Possibilities for Abatement. Energies 2018; 11(5): 1096.

[62] Jiang R, Zhou YL, Li RG. Moving to a Low-Carbon Economy in China: Decoupling and Decomposition Analysis of Emission and Economy from a Sector Perspective. Sustainability 2018; 10(4): 978.

[63] Zhao M-M, Li R. Decoupling and decomposition analysis of carbon emissions from economic output in Chinese Guangdong Province: A sector perspective. Energy & Environment 2018; 29: 543-555.

[64] Kang J, Zhao T, Liu N, Zhang X, Xu X, Lin T. A multi-sectoral decomposition analysis of city-level greenhouse gas emissions: Case study of Tianjin, China. Energy 2014; 68: 562-571.

[65] Wang M, Feng C. Using an extended logarithmic mean Divisia index approach to assess the roles of economic factors on industrial CO_2 emissions of China. Energy Economics 2018; 76: 101-114.

[66] Kroeze C, Vlasblom J, Gupta J, Boudri C, Blok K. The power sector in China and India: greenhouse gas emissions reduction potential and scenarios for 1990-2020. Energy Policy 2004; 32: 55-76.

[67] Wang K, Wang C, Lu XD, Chen JN. Scenario analysis on CO_2 emissions reduction potential in China's iron and steel industry. Energy Policy 2007; 35: 2320-2335.

[68] Cai WJ, Wang C, Wang K, Zhang Y, Chen J. Scenario analysis on CO_2 emissions reduction potential in China's electricity sector. Energy Policy 2007; 35: 6445-6456.

[69] Steenhof PA. Decomposition for emission baseline setting in China's electricity sector. Energy Policy 2007; 35: 280-294.

[70] Cai WJ, Wang C, Chen JN, Wang K, Zhang Y, Lu XD. Comparison of CO_2 emission scenarios and mitigation opportunities in China's five sectors in 2020. Energy Policy 2008; 36: 1181-1194.

[71] Zhu B, Zhou WJ, Hu SY, Li QA, Griffy-Brown C, Jin Y. CO_2 emissions and reduction potential in China's chemical industry. Energy 2010; 35: 4663-4670.

[72] Akashi O, Hanaoka T, Matsuoka Y, Kainuma M. A projection for global CO_2 emissions from the industrial sector through 2030 based on activity level and technology changes. Energy 2011; 36: 1855-1867.

[73] Lei Y, Zhang Q, Nielsen C, He K. An inventory of primary air pollutants and CO_2 emissions from cement production in China, 1990–2020. Atmospheric Environment 2011; 45: 147-154.

[74] Hara K, Yabar H, Uwasu M, Zhang HY. Energy intensity trends and scenarios for China's industrial sectors: a regional case study. Sustainability Science 2011; 6: 123-134.

[75] Chen Q, Kang C, Xia Q, Guan D. Preliminary exploration on low-carbon technology roadmap of China's power sector. Energy 2011; 36: 1500-1512.

[76] Ke J, Zheng N, Fridley D, Price L, Zhou N. Potential energy savings and CO_2 emissions reduction of China's cement industry. Energy Policy 2012; 45: 739-751.

[77] Hasanbeigi A, Morrow W, Sathaye J, Masanet E, Xu TF. A bottom-up model to estimate the energy efficiency improvement and CO_2 emission reduction potentials in the Chinese iron and steel industry. Energy 2013; 50: 315-325.

[78] Zhou S, Kyle GP, Yu S, Clarke LE, Eom J, Luckow P, Chaturvedi V, Zhang XL, Edmonds JA. Energy use and CO_2 emissions of China's industrial sector from a global perspective. Energy Policy 2013; 58: 284-294.

[79] Tian YH, Zhu QH, Geng Y. An analysis of energy-related greenhouse gas emissions in the Chinese iron and steel industry. Energy Policy 2013; 56: 352-361.

[80] Chen WY, Yin X, Ma D. A bottom-up analysis of China's iron and steel industrial energy consumption and CO_2 emissions. Applied Energy 2014; 136: 1174-1183.

[81] Li Y, Zhu L. Cost of energy saving and CO_2 emissions reduction in China's iron and steel sector. Applied Energy 2014; 130: 603-616.

[82] Lin BQ, Long HY. Promoting carbon emissions reduction in China's chemical process industry. Energy 2014; 77: 822-830.

[83] Liu LW, Zong HJ, Zhao ED, Chen CX, Wang JZ. Can China realize its carbon emission reduction goal in 2020: From the perspective of thermal power development. Applied Energy 2014; 124: 199-212.

[84] Wen ZG, Li HF. Analysis of potential energy conservation and CO_2 emissions reduction in China's non-ferrous metals industry from a technology perspective. International Journal of Greenhouse Gas Control 2014; 28: 45-56.

[85] Wen ZG, Meng FX, Chen M. Estimates of the potential for energy conservation and CO_2 emissions mitigation based on Asian-Pacific Integrated Model (AIM): the case of the iron and steel industry in China. Journal of Cleaner Production 2014; 65: 120-130.

[86] Wen ZG, Zhang X, Chen JN, Tan QL, Zhang XY. FORECASTING CO_2 MITIGATION AND POLICY OPTIONS FOR CHINA'S KEY SECTORS IN 2010-2030. Energy & Environment 2014; 25: 635-659.

[87] Xu JH, Fleiter T, Fan Y, Eichhammer W. CO_2 emissions reduction potential in China's cement industry compared to IEA's Cement Technology Roadmap up to 2050. Applied Energy 2014; 130: 592-602.

[88] Lin BQ, Ouyang XL. Analysis of energy-related CO_2 (carbon dioxide) emissions and reduction potential in the Chinese non-metallic mineral products industry. Energy 2014; 68: 688-697.

[89] Wang C, Ye MH, Cai WJ, Chen JN. The value of a clear, long-term climate policy agenda: A case study of China's power sector using a multi-region optimization model. Applied Energy 2014; 125: 276-288.

[90] Gao CK, Wang D, Zhao BH, Chen S, Qin W. Analyzing and forecasting CO_2 emission reduction in China's steel industry. Frontiers of Earth Science 2015; 9: 105-113.

[91] Wang ZH, Wang C, Yin JH. Strategies for addressing climate change on the industrial level: affecting factors to CO_2 emissions of energy-intensive industries in China. Natural Hazards 2015; 75: S303-S317.

[92] Wen ZG, Chen M, Meng FX. Evaluation of energy saving potential in China's cement industry using the Asian-Pacific Integrated Model and the technology promotion policy analysis. Energy Policy 2015; 77: 227-237.

[93] Yan X, Fang YP. CO_2 emissions and mitigation potential of the Chinese manufacturing industry. Journal of Cleaner Production 2015; 103: 759-773.

[94] Gu B, Tan X, Zeng Y, Mu Z. CO_2 Emission Reduction Potential in China's Electricity Sector: Scenario Analysis Based on LMDI Decomposition. Energy Procedia 2015; 75: 2436-2447.

[95] Wen ZG, Zhang X, Yu XW, Di JH. Technology options for reducing CO_2 in China's electricity sector in 2010-2030: From the perspective of internal and social costs. Greenhouse Gases-Science and Technology 2015; 5: 772-785.

[96] Li N, Ma D, Chen W. Projection of Cement Demand and Analysis of the Impacts of Carbon Tax on Cement Industry in China. Energy Procedia 2015; 75: 1766-1771.

[97] Sun W, Meng M, He YJ, Chang H. CO_2 Emissions from China's Power Industry: Scenarios and Policies for 13th Five-Year Plan. Energies 2016; 9(10): 825.

[98] Wang J, Zhao T, Wang YN. How to achieve the 2020 and 2030 emissions targets of China: Evidence from high, mid and low energy-consumption industrial sub-sectors. Atmospheric Environment 2016; 145: 280-292.

[99] Wang XL, Lin BQ. How to reduce CO_2 emissions in China's iron and steel industry. Renewable & Sustainable Energy Reviews 2016; 57: 1496-1505.

[100] Wu QL, Peng CY. Scenario Analysis of Carbon Emissions of China's Electric Power Industry Up to 2030. Energies 2016; 9(12): 988.

[101] Wu XC, Zhao L, Zhang YX, Zhao LJ, Zheng CH, Gao X, Cen KF. Cost and potential of energy conservation and collaborative pollutant reduction in the iron and steel industry in China. Applied Energy 2016; 184: 171-183.

[102] Yang LS, Lin BQ. Carbon dioxide-emission in China's power industry: Evidence and policy implications. Renewable & Sustainable Energy Reviews 2016; 60: 258-267.

[103] Yan Q, Zhang Q, Zou X. Decomposition analysis of carbon dioxide emissions in China's regional thermal electricity generation, 2000–2020. Energy 2016; 112: 788-794.

[104] Yuan JH, Na CN, Hu Z, Li P. Energy Conservation and Emissions Reduction in China's Power Sector: Alternative Scenarios Up to 2020. Energies 2016; 9(4): 266.

[105] Cui EQ, Ren LJ, Sun HY. Analysis of energy-related CO_2 emissions and driving factors in five major energy consumption sectors in China. Environmental Science and Pollution Research 2016; 23: 19667-19674.

[106] Xie X, Shao S, Lin BQ. Exploring the driving forces and mitigation pathways of CO_2 emissions in China's petroleum refining and coking industry: 1995-2031. Applied Energy 2016; 184: 1004-1015.

[107] Xu JH, Yi BW, Fan Y. A bottom-up optimization model for long-term CO_2 emissions reduction pathway in the cement industry: A case study of China. International Journal of Greenhouse Gas Control 2016; 44: 199-216.

[108] Zhang CQ, Zhang M, Zhang N. Identifying the Determinants of CO_2 Emission Change in China's Power Sector. Discrete Dynamics in Nature and Society 2016; 2626418.

[109] Chen CF, Han J. Energy conservation, emission reduction and win-win development of China's industry: 2013-2050-MDI analysis framework based on directional distance function. Applied Economics Letters 2016; 23: 1187-1191.

[110] Khanna NZ, Zhou N, Fridley D, Ke J. Quantifying the potential impacts of China's power-sector policies on coal input and CO_2 emissions through 2050: A bottom-up perspective. Utilities Policy 2016; 41: 128-138.

[111] Yao L, Liu JR, Zhou T, Wang RS. An analysis of the driving forces behind pollutant emission reduction in Chinese industry. Journal of Cleaner Production 2016; 112: 1395-1400.

[112] Zheng JJ, Jiang P, Qiao W, Zhu Y, Kennedy E. Analysis of air pollution reduction and climate change mitigation in the industry sector of Yangtze River Delta in China. Journal of Cleaner Production 2016; 114: 314-322.

[113] Lin BQ, Tan RP. Sustainable development of China's energy intensive industries: From the aspect of carbon dioxide emissions reduction. Renewable & Sustainable Energy Reviews 2017; 77: 386-394.

[114] Liu XB, Fan YB, Wang C. An estimation of the effect of carbon pricing for CO_2 mitigation in China's cement industry. Applied Energy 2017; 185: 671-686.

[115] Meng M, Jing KQ, Mander S. Scenario analysis of CO_2 emissions from China's electric power industry. Journal of Cleaner Production 2017; 142: 3101-3108.

[116] Wei PB, Cui HR, Gang MQ. Scenario analysis of energy conservation and CO_2 emissions reduction policies in China's iron and steel sector. Polish Journal of Environmental Studies 2017; 26: 2307-2317.

[117] Xuan YN, Yue Q. Scenario analysis on resource and environmental benefits of imported steel scrap for China's steel industry. Resources Conservation and Recycling 2017; 120: 186-198.

[118] Zhang X, Zhao XR, Jiang ZJ, Shao S. How to achieve the 2030 CO_2 emission-reduction targets for China's industrial sector: Retrospective decomposition and prospective trajectories. Global Environmental Change-Human and Policy Dimensions 2017; 44: 83-97.

[119] Zhao QZ, Yan QY, Cui HR, Zhao HR. Scenario Simulation of the Industrial Sector Carbon Dioxide Emission Reduction Effect. Polish Journal of Environmental Studies 2017; 26: 2841-2850.

[120] Zhao YH, Li H, Zhang ZH, Zhang YF, Wang S, Liu Y. Decomposition and scenario analysis of CO_2 emissions in China's power industry: based on LMDI method. Natural Hazards 2017; 86: 645-668.

[121] Gao TM, Shen L, Shen M, Liu LT, Chen FN, Gao L. Evolution and projection of CO_2 emissions for China's cement industry from 1980 to 2020. Renewable & Sustainable Energy Reviews 2017; 74: 522-537.

[122] Li W, Lu C, Ding Y, Zhang YW. The impacts of policy mix for resolving overcapacity in heavy chemical industry and operating national carbon emission trading market in China. Applied Energy 2017; 204: 509-524.

[123] Ge XL, Wang Y, Zhu HQ, Ding ZQ. Analysis and forecast of the Tianjin industrial carbon dioxide emissions resulted from energy consumption. International Journal of Sustainable Energy 2017; 36: 637-653.

[124] Li MQ, Patino-Echeverri D. Estimating benefits and costs of policies proposed in the 13th FYP to improve energy efficiency and reduce air emissions of China's electric power sector. Energy Policy 2017; 111: 222-234.

[125] Li N, Ma D, Chen WY. Quantifying the impacts of decarbonisation in China's cement sector: A perspective from an integrated assessment approach. Applied Energy 2017; 185: 1840-1848.

[126] Zhu XH, Zou JW, Feng C. Analysis of industrial energy-related CO_2 emissions and the reduction potential of cities in the Yangtze River Delta region. Journal of Cleaner Production 2017; 168: 791-802.

[127] An R, Yu B, Li R, Wei Y-M. Potential of energy savings and CO_2 emission reduction in China’s iron and steel industry. Applied Energy 2018; 226: 862-880.

[128] Li MJ, Mi ZF, Coffman D, Wei YM. Assessing the policy impacts on non-ferrous metals industry's CO_2 reduction: Evidence from China. Journal of Cleaner Production 2018; 192: 252-261.

[129] Wei J, Cen K, Geng Y. Evaluation and mitigation of cement CO_2 emissions: projection of emission scenarios toward 2030 in China and proposal of the roadmap to a low-carbon world by 2050. Mitigation and Adaptation Strategies for Global Change 2018; 24(2): 301-328.

[130] Zhang Q, Xu J, Wang YJ, Hasanbeigi A, Zhang W, Lu HY, Arens M. Comprehensive assessment of energy conservation and CO_2 emissions mitigation in China's iron and steel industry based on dynamic material flows. Applied Energy 2018; 209: 251-265.

[131] Zhou S, Wang Y, Yuan ZY, Ou XM. Peak energy consumption and CO_2 emissions in China's industrial sector. Energy Strategy Reviews 2018; 20: 113-123.

[132] Zhao YH, Li H, Xiao YL, Liu Y, Cao Y, Zhang ZH, Wang S, Zhang YF, Ahmad A. Scenario analysis of the carbon pricing policy in China's power sector through 2050: Based on an improved CGE model. Ecological Indicators 2018; 85: 352-366.

[133] Zhang D, Liu P, Ma L, Li Z, Ni W. A multi-period modelling and optimization approach to the planning of China's power sector with consideration of carbon dioxide mitigation. Computers & Chemical Engineering 2012; 37: 227-247.

[134] Tang B-J, Li R, Li X-Y, Chen H. An optimal production planning model of coal-fired power industry in China: Considering the process of closing down inefficient units and developing CCS technologies. Applied Energy 2017; 206: 519-530.

[135] Zhang N, Hu Z, Shen B, He G, Zheng Y. An integrated source-grid-load planning model at the macro level: Case study for China's power sector. Energy 2017; 126: 231-246.

[136] International Energy Agency (IEA), 2017. World Energy Outlook 2017. Avaialble from: < https://www.iea.org/weo2017/>.

Chapter 6

Conclusions and Discussion

This thesis studied in depth the energy use and CO_2 emissions of the industrial sector in China. Being responsible for about 84% of the Chinese CO_2 emissions in 2015, the industrial sector plays a vital role in achieving the emission goals for China. A main research question was proposed as illustrated in Chapter 1: *Has the industrial sector in China effectively been decarbonizing in recent years, across different regions and subsectors, and is it plausible that it will reduce its CO_2 emissions in conformity with national and internationally pledged emission goals?*

Due to the different energy-source mixes, uses and economic development needs, the comparisons among industrial sectors in 30 provinces will identify the key components for each province that should be improved in order to achieve the reduction of overall industrial CO_2 emissions. This can provide policymakers with a basis of formulating policies from a provincial/regional perspective. Chapter 2 addressed this question by ranking the carbon intensity of industrial sector in each province and identifying its drivers (energy intensity, energy mix and emission coefficient). From another perspective, the industrial sector is an integration of many sub-sectors, and the CO_2 emissions reduction of overall industrial sector will be dependent on the performance of each sub-sector. Due to the disparities in products and technologies among different industrial sub-sectors, differentiated policies at sector-level are necessary. Chapter 3 answered this question, where the driving forces of industrial aggregate energy intensity (IAEI) and the contribution of each industrial sub-sector to the IAEI were investigated. Chapter 2 showed that there were significant differences in carbon intensities and their driving forces among provinces. Chapter 3 indicated that the energy-intensive industries played important roles in shaping the IAEI. Based on the answers obtained from Chapters 2 and 3, we want to know what will happen to the CO_2 emissions and carbon intensity of energy-intensive industries if regional differences disappeared (regional convergence was achieved). Therefore, Chapter 4 studied to what extent convergence of performance of energy-intensive industries across provinces can contribute to CO_2 emission reductions and emission goals. After studying the historical drivers from regional and sector perspectives as well as the contribution of energy-intensive industries to the emissions goals, a systematic understanding of industrial CO_2 emissions is of great interest. Thus, Chapter 5 was born. Chapter 5 provided a critical literature review on the driving forces for the historical industrial CO_2 emissions and the projected ranges for future emissions, against the backdrop of policy goals, both for the industrial sector as a whole, and for the major industrial sub-sectors (electricity generation, cement production, steel production, chemicals, petroleum and non-ferrous metals). In combination, Chapter 2-5 presented a series of studies that aimed to answer the main research question.

Section 6.1 will now discuss the answers on the specific research questions and then come back on this main research question. This is followed by a discussion in section 6.2, followed by an outlook and suggestions for further research in section 6.3.

6.1 Conclusions

SQ1. *What are the spatial differences in carbon intensity across the provinces in China? What are the differences in driving forces across provinces? What patterns will emerge in the spatial clusters formed when provinces are grouped using spatial autocorrelation?*

Using spatiotemporal decomposition analysis, the carbon intensity of industrial sectors in different provinces was decomposed reflecting the changes in energy intensity, energy mix and emission coefficients. The industrial aggregate carbon intensity (IACI) and its drivers within each province were compared to the national average level, allowing to rank provinces in terms of IACI from a spatial perspective and in terms of the changes in IACI over time from a temporal perspective. From a spatial perspective, the results show that Beijing, Tianjin, Shanghai and Guangzhou performed best, exhibiting an IACI well below the national average. In contrast, the IACI of Hebei, Shanxi, Inner Mongolia, Ningxia and Xinjiang was much higher than the national average during the study period. Changes in the energy mix of Heilongjiang performed the best and contributed most to the decrease in IACI, but in contrast led to a high increase in IACI of Ningxia. By comparing to the national average level, changes in emission coefficients contributed the most to the reduction of IACI in Qinghai, Hubei, Yunnan and Sichuan while this factor contributed the most to the increase IACI in Heilongjiang, Inner Mongolia and Jilin. From a temporal perspective, the IACI declined in 28 provinces (i.e. all 30 Chinese provinces, except Ningxia and Xinjiang). Changes in the energy mix and emission coefficients had relatively small impacts on IACI. In Hainan changes in the energy mix had the highest contribution to IACI reductions (-25.15%) while Sichuan showed the highest contributions from reduced emission coefficients (-24.81%). The patterns of energy intensity effect played a decisive role in shaping the IACI both from the spatial and temporal perspectives.

Taking GDP per capita and geographic location into consideration, the 30 provinces were divided into four clusters: provinces with high (H) or low (L)levels of economic development (GDP per capita), which are surrounded by provinces with high (H) or low (L) levels of economic development, are abbreviated as HH, HL, LH and LL. By decomposing the IACI of these four clusters, it could be shown that provinces with high levels of economic development reduced their IACI most and if their adjacent provinces were less-developed, they reduced it even more.

SQ2. *What factors drive the changes in aggregate energy intensity of the industrial sector? What is the contribution of industrial sub-sectors to the changes in aggregate energy intensity?*

An extended decomposition analysis was conducted at the sectoral level to study the impacts on industrial aggregate energy intensity (IAEI) by various macroeconomic and technological factors. Such factors included sectoral energy intensity, industry structure, R&D efficiency, R&D intensity and investment intensity. Unlike earlier studies, this study found that the R&D efficiency (-76%) was the dominant factor contributing to the decrease in IAEI. This was followed by the effects of sectoral energy intensity (-27.2%) and industry structure (-16%). Conversely, the investment intensity and R&D intensity largely contributed to an increase in IAEI, with values of 174.1% and 52.1%, respectively. However, the effects of investment intensity and R&D intensity are more than offset by the effects of R&D efficiency, sectoral energy intensity and industrial structure. Their combined effects led to an overall decrease in IAEI by 38.3% from 2003 to 2015.

To identify the adaptability and sensitivity of various industrial sub-sectors, the effects of sectoral energy intensity, industrial structure, R&D efficiency, R&D intensity and investment intensity were attributed to 36 industrial sub-sectors. The results showed that 35 sub-sectors (excluding *gas production and supply*) contributed to the decrease in IAEI through R&D efficiency, of which the sub-sectors of *ferrous metals* (-14.9%) and *non-metallic mineral products* (-13.4%) contributed the most. The energy intensity of five sub-sectors went up, especially *plastic products* and *non-metallic mineral products* while the sub-sectors of *ferrous metals* (−16%) and *non-ferrous metals* (−5.7%) contributed the most to the decrease in IAEI though sectoral energy intensity effect. The industrial structure effect was largely attributed to the sub-sectors of *petroleum, coking and nuclear fuel* (−5.6%) and *ferrous metals* (−4.7%). 29 industrial sub-sectors contributed to the increase in IAEI through investment intensity, of which *non-metallic mineral products* (40.8%) and *chemical materials* (28.5%) were the largest contributors. The sub-sectors of *non-metallic mineral products* and *ferrous metals* saw an increase in IAEI by 17. 8% and 10.5%, respectively, through R&D intensity.

In sum, the findings indicate that the IAEI decreased from 2003 to 2015 with 38.3%, but also that different sub-sectors in the Chinese energy-intensive industry play a different role in this overall reduction. Therefore, different policies and measures should be put forward in different sub-sectors due to their varying degrees of adaptability and policy sensitivity.

SQ3. *What is the contribution of regional convergence in energy-intensive industries to CO_2 emissions reduction and to the emissions goals of China?*

In order to address this research question, three scenarios were developed to reflect different levels of regional convergence: (1) a business as usual (BAU) scenario, in which the historical regional convergence will continue; (2) a frontier scenario, which is established based on the DDF (directional distance function) method, and is used to reflect a weak form of regional convergence, in which provinces approach an efficiency frontier, where the provinces perform well in emissions abatement while keep the industrial output growth; and (3) a best available technology (BAT) scenario, in which all provinces will realize the emission levels per unit of output of the best-in-class province, representing a strong form of regional convergence.

The CO_2 emissions in the three scenarios are predicted based on the Kaya identity. By comparing the CO_2 emissions and the carbon intensity under the frontier and BAT scenarios to those in BAU, the potential contribution of regional convergence to CO_2 emissions and emissions goals can be calculated. The results show that the CO_2 emissions in energy-intensive industries can be reduced with about 43% if the frontier scenario can be realized in 2030. The reduction potential will be more than 80% if the BAT scenario is reached. The reduction potentials of the *electricity* and *ferrous metals* sectors are the most significant due to their high absolute emissions and the heterogeneities across provinces. For the COP21 in Paris, China has pledged in its INDCs (Intended Nationally Determined Contributions) to peak its CO_2 emissions by 2030. The results indicate that the CO_2 emissions of energy-intensive industries cannot reach the peak before 2030 under a BAU scenario. The emissions however could peak in 2025 if there was regional convergence, either in the weak or strong forms. With the energy-intensive industries being responsible for 79% of China's total emissions in 2015, realizing their peak emissions before 2030 is crucial for realizing the aforementioned INDCs. China also pledged to reduce its carbon intensity by 40-45% in 2020 and 60-65% in 2030. The energy-intensive industries can achieve these reduction goals 2020 and 2030 even in the BAU scenario. If regional convergence occurs, more ambitious reductions in carbon intensity can be obtained. For energy-intensive sub-sectors, the *electricity* sector cannot achieve the reduction goals of 40-45% by 2020 and 60-65% by 2030 in the BAU scenario, while the goals can be realized under the frontier and BAT scenarios.

SQ4. *What are the patterns of historical drivers for the changes in industrial CO_2 emissions in China as identified in the existing scientific literature? What projections for future CO_2 emissions of industrial sector and its major sub-sectors are provided in the scientific literature? And how will policy goals affect the industrial emissions in the future?*

To answer this research question, first 65 studies were collected that analyzed the historical drivers for industrial CO_2 emissions in China. These studies explored many drivers of industrial CO_2 emissions, including industrial activity, energy intensity, energy mix, emission coefficients and industry structure. In general, increase in industrial activity was identified as the most important factor driving the increase in industrial CO_2 emissions after 2000. Improvement of emissions coefficients had a marginal influence on the reduction of industrial CO_2 emissions. However, various other factors contributed to relative emission reductions since 2013. The most important factor was a reduction in energy intensity. Also a change in the energy mix contributed to the decrease in industrial emissions, particularly after 2012. Since China has policy targets to increase low-carbon energy use until 2020, changes in the energy mix will lead to further emission reductions in the future. Changes in the industry structure had both positive and negative effects on emissions before 2007. After 2007, changes in industry structure contributed to a reduction of carbon emissions. Since China embarks on ambitious efforts to restrict energy-intensive industries and promote green manufacturing as well as high value-added industries, further shifts in the industrial structure will support further emission reductions in the future.

Next, 70 papers were collected that discussed projections of CO_2 emissions in China's industrial sector and its major sub-sectors. From the highest projections per sub-sector across studies, a BAU scenario was constructed. From the lowest projections per sub-sector across studies, an optimistic scenario was constructed. A medium scenario was constructed as the median projection over all other scenarios (so excluding the BAU and optimistic scenarios) reported in the literature collected if there were more than two remaining scenarios in one study. This analysis did not compare projections of the carbon intensity with national or international intensity reduction goals. The reason for this is that the carbon intensity in different industrial sub-sectors is measured in different ways, which are not always consistent the definitions in national targets or international pledges (CO_2 emissions per unit of IVA for the industrial sector). The assessment did show however that the median CO_2 emissions of industrial sector will likely peak in 2030 in the BAU and medium scenarios. This is in line with China's INDCs as committed to the COP21 in Paris in 2015. If the optimistic scenario is realized, the peak of industrial emissions already took place in the past, i.e. 2013. Zooming in on industrial sub-sectors, the following picture arises. For the *electricity* sector, the median CO_2 emissions will increase until 2030 in the three scenarios, indicating that it is less likely for the *electricity* sector to reach the emissions peak before 2030. For the *ferrous metals* and *nonmetallic product* sectors, the median CO_2 emissions in three scenarios will decline until 2050, even the maximum emissions also will decline except for 2020, meaning that their emissions peak will be reached in 2020 or even in 2013. Policies and regulations as laid down in e.g. plans like the *13th FYP (Five-Year-Plan), China Industrial Green*

Development (2016-2020) and *Made in China 2025* will further ensure that national and international carbon reduction commitments will be met.

Based on the answers to the sub-questions, now a positive answer can be given to the overall research question: *Has the industrial sector in China effectively been decarbonizing in recent years, across different regions and subsectors, and is it plausible that it will reduce its CO_2 emissions in conformity with national and internationally pledged emission goals?* After a rapid growth over the past decade, the China's industrial CO_2 emissions decreased since 2013, while the industrial aggregate carbon intensity showed a sustained decline, indicating that the decarbonization measures helped. Chapter 2 (answering SQ1) suggested that the measures for improving energy efficiency were the most important steps to reduce the industrial aggregate carbon intensities as energy intensity was the most important factor in shaping the industrial aggregate carbon intensity for all provinces. Herein, the energy intensity in Xinjiang, Ningxia and Shanxi should be greatly improved. As a complement to Chapter 2, Chapter 3 (answering SQ2) showed that the sensitivity and adaptability of each industrial sub-sector to the policies were different, and the energy intensity in *petroleum, plastic products* and *non-metallic products* sectors should be the focus of improvement. In Chapter 4 (answering RQ3) it could be shown that under a frontier scenario and a BAT scenario, where sectors in different provinces converge in terms of carbon-intensity, overall CO_2 emission reductions of 43% and 80% for energy-intensive industries could be realized, respectively, in 2030. This result indicated that the regional convergence should be encouraged in energy-intensive industries, where the regional convergence can be achieved by technological diffusion from advanced provinces to backward provinces. Also the meta-review conducted in Chapter 5 (answering RQ4) on historical drivers and future projections give reasons for careful optimism. Even in the BAU scenario, which is the most pessimistic across all forecasts, the Chinese industrial sector is likely to peak its CO_2 emissions by 2030. When the median emissions of the optimistic projections across studies are taken, China's industrial emission peak is likely already have taken place in the past. The assumptions behind the optimistic scenarios mainly focused on the important historical drivers obtained in Chapter 2 and Chapter 3, such as improvement of energy efficiency (intensity), shifts in energy structure (encouragement of renewables) and industrial structure (from energy-intensive industrial sub-sectors towards high value added industrial sub-sectors). What should be emphasized was that these policies should be implemented considering the disparities of provinces and sub-sectors, thus it will be more conducive to the achievement of overall industrial emissions targets.

6.2 Discussion

A spatiotemporal decomposition analysis was used to compare the IACI and its driving forces of the industrial sector in 30 provinces in China. In this method, a reference province should be constructed. The choice can be made to use an existing province or a hypothetical one. If the gaps between the best performing province and the remaining provinces are of interest, the best performing province can be used as reference. If only a general ranking of provinces is desired, then the national average (arithmetic or weighted average) can be regarded as the benchmark. A spatiotemporal decomposition can rank provinces in terms of the IACI, energy intensity, industrial structure or energy mix, information that can provide a basis for policy recommendations. For example, China's overall emissions goals should be the sum of the provincial ones. The provincial targets could take into account their current CO_2 emissions, but also their carbon intensity. For instance, for developed provinces or municipalities, such as Beijing, Tianjin and Shanghai an emissions cap could be set. At the same time, less developed provinces with high carbon intensities, such as Shanxi, Ningxia and Xinjiang, could be allowed to reach their emissions peak later. Such provinces then can reduce their emission intensity and at the same time still grow economic output significantly. By differentiating targets by province in this way, national emission goals can be realized easier.

Regional convergence can contribute significantly to a reduction in CO_2 emissions of China's energy-intensive industries, and can support the realization of an emission peak around 2025. However, there might be some reasons, such as resource endowments and the remaining economic life-time of industrial installations, that may prevent the realization of regional convergence. The *electricity* sector can be regarded as an example. There are different technologies for power generation, such as thermal power, hydropower, nuclear power, wind power and solar power. The potential deployment of low-carbon energy technologies depend however strongly on geographical and weather conditions. Their deployment hence shows a clear regional distribution. Hydropower is concentrated mainly in southwest region and Hubei province; nuclear power is mainly located in Zhejiang, Fujian and Guangdong; wind power is based in the north of China; and solar power is mainly deployed in the Yangtze River Delta, Bohai Rim and western regions. Thus, it is difficult for all provinces to converge the same optimal power mix due to differences in local resource endowments. However, it hast to be noted too thermal power generation is still dominant in most provinces and the efficiency of these thermal power plants varies across provinces. For example, emission factors (CO_2 emissions per unit of power generation) of thermal power plants in Inner Mongolia are 20% higher than that in Guangdong (Liu et al., 2018). This means that there exists room for regional convergence though low-carbon technology diffusion across provinces for a specific sector, where the regional convergence could result in emissions reduction.

China's industrial CO_2 emissions grew from 2.5 Gt/yr in 2000 to 8.2 Gt/yr in 2013 with an annual growth rate of 9.7%, and decreased thereafter to 7.8 Gt/yr in 2015 (7.1 Gt/yr from energy consumption and 0.7 Gt/yr from cement production) (CEADs, 2018). Continuous decrease in energy intensity, a lower use of coal and shifts in industrial structure towards high-value added industries were the three major factors for this decrease. If this decrease in industrial CO_2 emissions could be maintained, China's commitment to the Paris Agreement is likely to be achieved, because the industrial sector accounted for 84% of national emissions in 2015. However, industrial emissions may fluctuate in the coming years. Chapter 5 shows that the industrial emissions are likely to peak in 2030. The emissions of the *electricity* sector may still increase afterwards, but this is compensated by reductions in e.g. the *ferrous metals* and *nonmetallic products* sectors. In addition to the factors studied in this thesis (e.g., energy efficiency, energy mix, industrial structure, industrial activity and pollutant reduction) which are subject to clear targets set in Chinese policy plans, additional decarbonization measures can be been deployed. Examples are carbon capture storage (CCS) and the deployment of a national emissions trading system (ETS) (ADB, 2015; Springer et al., 2019). The most important target sectors for CCS are fossil-fuel intensive industries, such as petrochemicals, ferrous metals and thermal power plants. China has produced a roadmap for CCS deployment. This roadmap assumed an emission reduction by CCS of 10 Mt/yr in 2020, 40Mt/yr in 2030, 440 Mt/yr in 2040 and 2400 Mt/yr in 2050 (ADB, 2015). China has also established a national ETS at the end of 2017. The electricity sector is at this point the only sector covered. The deployment of CCS and the ETS may result in an earlier emissions peak of China's industrial sector as suggested in this thesis.

6.3 Outlook

This study explored the driving forces of the evolution in historical industrial energy use and carbon emissions in China from a regional and sectoral perspective. Next to this, how the industrial sector and its sub-sectors could contribute to China's CO_2 emissions goals in 2020 and 2030 was investigated. However, there are still several topics that can be studied in further work.

In recent years, industry relocation, especially in manufacturing, has become an important topic of research (Chen et al., 2017). Industry relocation is in principle an effective way to optimize the spatial distribution of the production system. Yet, it often results in shifting production from relatively developed countries (regions) to the relatively less developed countries (regions) (Chen et al., 2017). Historically, such 'offshoring' resulted in production being moved to countries (regions) with higher emission intensities, leading to an overall decrease in domestic carbon emissions per unit of output (Michel, 2013). Hence, if a more evenly distributed pattern of production will lead to a higher utilization efficiency of equipment and a reduction of transport, all potentially causing a decrease in CO_2 emissions, should be studied further. Even though Chen et al. (2017), Chen et al. (2018) and Pappaset et al. (2018) have discussed the impacts of industry transfer (relocation) and industrial agglomeration on CO_2 emissions, little details about the industry transfer (relocation) have been given. Therefore, future research could give more insights into the impacts of industry relocation on CO_2 emissions.

Another important area of research concerns aligning basic statistics. Both the IPCC and National Development and Reform Commission of China (NDRC) provide information on basic factors related to energy and emissions, such as the net caloric value of different energy carriers, and CO_2 emission factors per unit of caloric value per type of carriers. For China, such basic statistical information differs highly between these two data sources (Shan et al., 2018). The IPCC default emission factors are almost 40% higher than those provided by the NDRC (Liu et al., 2015). Such differences in emission coefficients will lead to huge over- or underestimations of China's CO_2 emissions and large uncertainties in estimates of global emissions. For example, the national CO_2 emissions from fossil fuels is 9.1 Gt/yr in 2015 by IEA while it is 8.6 Gt/yr by Shan et al. (2018). Obviously whether China will realize its emission goals is highly influenced by which data set used. Future work should be done to reduce the discrepancies in such basic data on the caloric value of energy carriers and emission factors.

Finally, studies providing projections of industrial CO_2 emissions should be updated. Most previous studies were not based on the latest data of the energy consumption, which implies that previous studies are not taking into account the declining trend of CO_2 emissions in 2014 and 2015. Additionally, previous studies may have underestimated future shifts in industrial structure. Recent policy plans such as *"13th FYP"*, "*China Industrial Green Development Plan 2016–2020*" and "*Made in China 2025*" restrict emissions of the energy-intensive industries by precise targets, and foresee a strong expansion of green manufacturing. Finally, in existing studies the substitution of low-carbon energy on fossil energy may also be underestimated. In the 13th FYP from 2016 to 2020 poses clear limits on the use of coal for energy production. Simultaneously, the 13th FYP for Electricity and Energy was issued in fall 2016, which included a number of capacity targets for different power generation technologies for 2020. Therefore, these recent policies should be taken into account in future studies that make projections of the carbon emissions of the industry sector in China.

References

Asia Development Bank (ADB), 2018. Research on China's carbon capture and storage demonstration and promotion roadmap. Available from: <roadmap-ccs-prc-zh.pdf>.

Chen DK, Chen SY, Jin H, 2018. Industrial agglomeration and CO_2 emissions: Evidence from 187 Chinese prefecture-level cities over 2005-2013. Journal of Cleaner Production 172: 993-1003.

Chen L, Xu LY, Yang ZF, 2017. Accounting carbon emission changes under regional industrial transfer in an urban agglomeration in China's Pearl River Delta. Journal of Cleaner Production 167: 110-119.

China Emission Accounts & Datasets (CEADs), 2018. Available from: <http://www.ceads.net/data/inventory-by-sectoral-approach/>

Liu Z, Guan DB, Moore S, Lee H, Su J, Zhang Q, 2018. Climate policy: Steps to China's carbon peak. Nature 522(7556): 279-281.

Liu Z, Guan DB, Wei W, Davis SJ, Ciais P, Bai J, et al., 2015. Reduced carbon emissions from fossil fuel combustion and cement production in China. Nature 524: 335-338.

Michel B, 2013. Does offshoring contribute to reducing domestic air emissions? Evidence from Belgian manufacturing. Ecological Economics 95: 73-82.

Pappas D, Chalvatzis KJ, Guan DB, Loannidis A, 2018. Energy and carbon intensity: A study on the cross-country industrial shift from China to India and SE Asia. Applied Energy 225: 183-194.

Shan YL, Guan DB, Zheng HR, Ou JM, Li Y, Meng J, Mi ZF, Liu Z, Zhang Q, 2018. China CO_2 emission accounts 1997-2015. Scientific Data 5: 170201.

Springer C, Evans S, Lin J, Roland-Holst D, 2019. Low carbon growth in China: The role of emissions trading in a transitioning economy. Applied Energy 235: 1118-1125.

Summary

Introduction

The Paris Agreement set a long-term temperature goal of holding the global average temperature increase to well below 2 °C and pursuing efforts to limit this to 1.5 °C above pre-industrial levels. Many previous researchers have identified that the relationship between global mean temperature change and cumulative CO_2 emissions is near-linear. Achieving a reduction in CO_2 emissions or even negative emissions is the main way to achieve the targets of Paris Agreement. Currently, China is the largest CO_2 emitter, accounting for 28.2% of the global emissions in 2015. In China, the industrial sector is the pillar of economic development and the most important sector of CO_2 emissions, making up about 40% of national GDP and 84% of national CO_2 emissions. Therefore, the CO_2 emissions of the industrial sector are important for China to achieve a lower growth or reduction in total emissions. As a prerequisite for carbon reduction, investigating the driving forces of CO_2 emissions is of significant importance. In view of the heterogeneities across regions and industrial sub-sectors, the driving forces should be studied from different perspectives. Besides, China promised that its carbon intensity will be reduced by 40-45% and 60-65% in 2020 and 2030, respectively, compared with the 2005 level, as well as that emissions will peak no later than 2030. Regarding whether China can achieve these emissions targets, the industrial sector plays a decisive role. Therefore, the future trajectories of carbon intensity and CO_2 emissions of industrial sector and its major sub-sectors are worth exploring.

Research questions

According to the abovementioned discussion, a main question and several key research questions can be extracted. These pertain to the driving force of historical industrial energy use and CO_2 emissions from regional and sectoral perspectives, as well as future CO_2 emissions/intensity. The main question is: *Has the industrial sector in China effectively been decarbonizing in recent years, across different regions and subsectors, and is it plausible that it will reduce its CO_2 emissions in conformity with national and internationally pledged emission goals?* The following four research questions are addressed:

SQ1. *What are the spatial differences in carbon intensity across the provinces in China? What are the differences in driving forces across provinces? What patterns will emerge in the spatial clusters formed when provinces are grouped using spatial autocorrelation?*

SQ2. *What factors drive the changes in aggregate energy intensity of the industrial sector? What is the contribution of industrial sub-sectors to the changes in aggregate energy intensity?*

SQ3. *What is the contribution of regional convergence in energy-intensive industries to CO_2 emissions reduction and to the emissions goals of China?*

SQ4. *What are the patterns of historical drivers for the changes in industrial CO_2 emissions in China as identified in the existing scientific literature? What projections for future CO_2 emissions of industrial sector and its major sub-sectors are provided in the scientific literature? And how will policy goals affect the industrial emissions in the future?*

Answers to research questions

Answers to SQ1. Chapter 2 presented a study on driving forces of industrial aggregate carbon intensity (IACI) from a regional perspective. Using a spatiotemporal decomposition analysis, the IACI was decomposed into three factors: energy intensity, energy structure and industrial structure. The IACI of each province was compared against the national average level, allowing us to capture both the rankings of provinces from a spatial and temporal perspectives. The results showed that Beijing, Tianjin, Shanghai and Guangdong were the best performers, and their IACI were 90.42%, 80.61%, 80.26% and 78.6% lower than the national average, respectively. From the temporal perspective, the IACI of Beijing, Chongqing, Tianjin and Hubei decreased the most with values of 88.11%, 76.73%, 75.35% and 74.71% from 1999 to 2015, respectively. Energy intensity was the decisive factor determining the patterns of carbon intensity. Based on spatial autocorrelation, we found that provinces with high levels of economic development performed well and if their adjacent provinces were less-developed, they performed even better.

Answers to SQ2. Chapter 3 developed a study considering the impacts of both macro and technological factors on the industrial aggregate energy intensity (IAEI). As a first step, the IAEI was decomposed into the factors of sectoral energy intensity, industrial structure, R&D efficiency, R&D intensity and investment intensity. Then, the contribution of industrial sub-sectors to the IAEI through each driver was explored. The results showed that the IAEI decreased by 38.26% from 2003 to 2015, of which the R&D efficiency, sectoral energy intensity and industrial structure contributed to -76.01%, -27.19% and -15.06%. However, the investment intensity and R&D intensity largely contributed to the increase in IAEI, with values of 174.09% and 52.06%, respectively. For each driving force, energy-intensive industries contributed the most, indicating that energy-intensive industries play an important role in the industrial sector as a whole.

Answers to SQ3. Chapter 3 established three scenarios, BAU (business as usual), frontier and BAT (best available technology) scenarios, to investigate the contribution of regional convergence in energy-intensive industries to CO_2 emissions and emissions goals, with each scenario reflecting a different form of regional convergence. The results showed that the CO_2 emissions of energy-intensive industries cannot reach the emissions peak before 2030 in BAU scenario, while the emissions peak will be achieved around 2025 in the frontier and BAT scenarios. As for carbon intensity, the 40-45% and 60-65% reduction targets can be realized by energy-intensive industries even in the BAU scenario, and the reduction proportions will be larger in the frontier and BAT scenarios. For energy-intensive sub-sectors, the reduction potentials of the electricity sector in both CO_2 emissions and carbon intensity were the most significant.

Answers to SQ4. Chapter 4 conducts a systematic literature review related to two major research streams, on is driving forces of CO_2 emissions and the other is the future trajectory of CO_2 emissions in industrial sector and its major sub-sectors. We found that a reduction in energy intensity was responsible for the decrease in industrial CO_2 emissions since 2000 while a rise in industrial activity was the dominant factor leading to an increase in CO_2 emissions. The effects of industrial structure and energy structure were mixed in the early years of the analysis, but the industrial structure turned to be a factor decreasing the CO_2 emissions after 2007 and the energy structure started to contributed the decrease in industrial CO_2 emissions after 2012. Based on the results of extensive studies, it can be found that the median CO_2 emissions of industrial sector will likely peak in 2030 (earlier in 2013 in the optimistic scenario), which is aligned with China's commitment to Paris Agreement. For industrial sub-sectors, the median emissions of *electricity* sector will increase until 2030 in three scenarios, while the median emissions of *ferrous metals* and *nonmetallic product* sectors will decline until 2050. The recent published policies are increasingly consistent with the Paris Agreement. If the targets of carbon intensity can be achieved, the industrial emissions in 2020 will be close to the median emissions in medium scenario and in 2030 will be within the median emissions between medium and optimistic scenarios.

Outlook

Industry relocation frequently occurs between China's provinces, especially the manufacturing industry shifting from developed provinces to the relatively underdeveloped provinces. This phenomenon is a byproducts of economic development, which could optimize the spatial layout of productivity and form a reasonable industrial division system. Therefore, the impact of industry relocation on the CO_2 emissions of the industrial sector as a whole is worth studying in the future.

Currently, there is no consistent emission coefficient (net caloric value and CO_2 emissions per net caloric value) for China's fossil fuels, where both IPCC and National Development and Reform Commission published the related data sets. Because the coefficient is a major component when estimating CO_2 emissions, its choice will lead to over- or under-estimation of CO_2 emissions. Thus, the assessment of whether China can achieve its emission goals will be affected. Therefore, this matter should be discussed in future work.

The projections of industrial CO_2 emissions should be updated. Most previous studies were not based on the latest data of the energy consumption, so the decline trend of CO_2 emissions in 2014 and 2015 is hardly captured. Several policy documents were issued in recent two years, such that industrial energy intensity, industrial structure and energy structure are now more strictly regulated. Therefore, the projections of industrial CO_2 emissions should be updated considering both the latest data set of energy consumption and the newest policies.

Samenvatting

Inleiding

In de Overeenkomst van Parijs inzake klimaatverandering is als lange termijn doelstelling afgesproken om de mondiale temperatuurstijging ruim onder de 2 °C te houden en ernaar te streven deze te beperken tot 1.5 °C boven het pre-industriële niveau. Onderzoek heeft vastgesteld dat de relatie tussen de mondiale gemiddelde temperatuurverandering en de cumulatieve CO_2-uitstoot bijna lineair is. Vergaande reductie van de CO_2-uitstoot of zelfs het realiseren van negatieve emissies zijn de belangrijkste manieren om de doelstellingen van de Overeenkomst van Parijs te bereiken. Momenteel is China de grootste emittent van CO_2, goed voor 28.2% van de wereldwijde uitstoot in 2015. In China is de industriële sector de belangrijkste factor achter de snelle economische ontwikkeling van het land, maar ook de belangrijkste bron van CO_2-emissies. De industriële sector is verantwoordelijk voor ongeveer 40% van het Chinese Bruto Binnenlands Product (BBP) en 84% van de Chinese CO_2-uitstoot. De industriële sector is daarom cruciaal indien China een vergaande vermindering van CO_2-uitstoot wil realiseren. Het is daarom van groot belang de drijvende krachten achter de historische groei van CO_2-emissies in de industriële sector te begrijpen. Omdat de industriële sector qua structuur en ook tussen regio's erg heterogeen is, :moeten deze drijvende krachten vanuit verschillende perspectieven worden bestudeerd. China heeft beloofd dat de CO_2-intensiteit van zijn economie met respectievelijk 40-45% en 60-65% in 2020 en 2030 zal worden verlaagd ten opzichte van het niveau van 2005, en dat de emissies uiterlijk in 2030 hun piek zullen hebben bereikt. Voor het bereiken van deze emissiedoelstellingen, speelt de industriële sector een cruciale rol. Het is dan ook van groot belang om de historische en toekomstige ontwikkelingen van de CO_2-intensiteit van de industriële sector in China, en zijn sub-sectoren, goed te analyseren.

Onderzoeksvragen

Op basis van bovenstaande inleiding kunnen nu een hoofdvraag en een aantal belangrijke sub-vragen voor onderzoek worden gesteld. Deze hebben betrekking op de drijvende krachten die het historisch industrieel energiegebruik en de historische CO_2-emissies vanuit regionaal en sectorperspectief verklaren, evenals de verwachtingen ten aanzien van de toekomstige CO_2-emissie-intensiteit. De hoofdvraag in dit proefschrift is dan ook: *heeft de industriële sector in China de afgelopen jaren een reductie in CO_2 en energie-intensiteit laten zien, in verschillende regio's en sub-sectoren, en is het plausibel dat verdergaande CO_2 reducties worden bereikt die in lijn zijn met nationale en internationaal afgesproken emissiedoelstellingen?* Hierbij worden de volgende sub-vragen (SV) gesteld:

SV1. Wat zijn de verschillen in CO_2-intensiteit tussen de verschillende provincies in China? Wat zijn de factoren / drijvende krachten die deze verschillen tussen provincies verklaren? Welke patronen zien we als we provincies clusteren op basis van ruimtelijke autocorrelatie?

SV2. Welke factoren verklaren de veranderingen in de geaggregeerde energie-intensiteit van de industriële sector? Wat is de bijdrage diverse subsectoren binnen de industrie aan de veranderingen in deze geaggregeerde energie-intensiteit?

SV3. Welke rol kan regionale convergentie in emissie-intensiteit van energie-intensieve industrieën spelen in het reduceren van CO_2-emissies en het realiseren van de emissiedoelstellingen van China?

SQ4. Wat zegt de bestaande wetenschappelijke literatuur over de drijvende krachten die historische veranderingen in de emissie-intensiteit van de Chinese industriële sector verklaren? Welke projecties geeft die wetenschappelijke literatuur voor de toekomstige CO_2-emissies van de industriële sector en zijn belangrijkste subsectoren? En hoe zullen beleidsdoelen de industriële emissies in de toekomst beïnvloeden?

Antwoorden op onderzoeksvragen

Antwoorden op SV1. Hoofdstuk 2 van dit proefschrift analyseert de drijvende krachten achter industriële CO_2-intensiteit vanuit een regionaal perspectief. Met behulp van een spatiotemporele decompositie-analyse is de industriële CO_2-intensiteit ontleed in drie factoren: energie-intensiteit, energiestructuur en industriële structuur. De industriële CO_2-intensiteit van elke provincie is vergeleken met het nationale gemiddelde niveau. De provincies konden zo gerangschikt worden vanuit een zowel een ruimtelijk als temporeel perspectief. De resultaten toonden aan dat Beijing, Tianjin, Shanghai en Guangdong de best presterende provincies waren. De industriële CO_2-intensiteit lag respectievelijk 90.42%, 80.61%, 80.26% en 78.6% onder het het nationale gemiddelde. Vanuit een temporeel perspectief blijkt dat tussen 1999 en 2015 de industriële CO_2-intensiteit het meest afnamen in Beijing, Chongqing, Heilongjiang en Hubei, met respectievelijk 82.85%, 76.49%, 73.82% en 70.62%. De energie-intensiteit was de belangrijkste factor in het reduceren van de CO_2 emissies. De ruimtelijke autocorrelatie toonde aan dat provincies met een hoog niveau van economische ontwikkeling hun CO_2-intensiteit het meeste verminderden, vooral indien hun aangrenzende provincies minder ontwikkeld waren.

Antwoorden op SV2. Hoofdstuk 3 analyseert welke factoren het meest van belang zijn in de ontwikkeling van de industriële geaggregeerde energie-intensiteit (IGEI). Als een eerste stap werd de IGEI geanalyseerd via een decompositie in de volgende factoren: sectorale energie-intensiteit, industriële structuur, efficiëntie van onderzoek en ontwikkeling, onderzoeks- en ontwikkelingsintensiteit en investeringsintensiteit. Vervolgens werd onderzocht welke factoren de bijdrage van industriële subsectoren aan de IGEI bepaalden. Uit de resultaten bleek dat de IGEI tussen 2003 en 2015 met 38,26% is gedaald. Hieraan droegen de efficiëntie van onderzoek en ontwikkeling, de sectorale energie-intensiteit en de industriële structuur bij met respectievelijk -76.01%, -27.19% en -15.06%. De investeringsintensiteit en de onderzoeks- en ontwikkelingintensiteit droegen juist bij aan een toename van de IGEI, met waarden van respectievelijk 174.09% en 52.06%.

Antwoorden op SV3. Hoofdstuk 4 analyseerde wat de bijdrage van regionale convergentie zou kunnen zijn aan het reduceren van de CO_2-emissieintensiteit van de industriële sector. In het hoofdstuk zijn drie scenario's onderscheiden: het BAU-scenario (business as usual), het frontier scenario, en het BAT (best available technology). Het BAT scenario neemt aan dat elke sub-sector in elke provincie de emissie-intensiteit van de sub-sector in de best presterende provincie bereikt. Het 'frontier' scenario neemt aan, dat elke sub-sector een optimale mix van input van productiefactoren en gewenste output en emissies bereikt. Het blijkt dat in het BAU scenario de industriële sector niet in staat zal zijn de beleidsdoelstelling van een emissiepiek vóór 2030 te bereiken. In het 'frontier' en BAT scenario wordt de CO_2-emissiepiek rond 2025 bereikt. In alle scenario's is het echter wel mogelijk de beleidsdoelstelling van 40-45% en 60-65% reductie van emissie-intensiteit per 2020 respectievelijk 2030 te bereiken. De reducties kunnen echter veel groter worden indien het ‘frontier’ of BAT scenario kan worden gerealiseerd. De elektriciteitssector is veruit dominant in termen van absolute CO_2 emissies en het reductiepotentieel.

Antwoorden op SV4. Hoofdstuk 5 geeft een systematisch literatuuronderzoek weer met betrekking tot twee belangrijke onderwerpen van onderzoek: de historische drijvende krachten achter CO_2-emissies en toekomstige verwachtingen ten aanzien van CO_2-emissies in de industriële sector en zijn belangrijkste subsectoren in China. We vonden dat een vermindering van de energie-intensiteit de belangrijkste oorzaak was van de daling van de industriële CO_2-emissies sinds 2000, terwijl een toename van de industriële activiteit de dominante factor was die leidde tot een toename van de CO_2-uitstoot. De effecten van wijzigingen van de structuur van de industrie en het energiegebruik hadden zowel positieve als negatieve invloed in de periode tot 2007. Na 2007 droeg een wijziging in de structuur van de industriële productie bij aan een afname van CO_2-emissies, en na 2012 gold hetzelfde voor de wijziging in de structuur van het energiegebruik .Literatuur ten aanzien van toekomstige emissies verwacht in het algemeen dat de emissies van de industriële sector hun piek zullen bereiken in uiterlijk 2030, wat spoort met de beloften die China deed in het kader van de Overeenkomst van Parijs. In de meest optimistische scenario’s heeft de piek van de industriële CO_2 emissies al in 2013 plaatsgehad. In alle scenario’s zien we de emissies van de elektriciteitssector tot 2030 toenemen, terwijl de emissies van de ferro- en niet-metaalproduct sectoren zullen afnemen tot 2050. Het Chinese beleid is in hoge mate consistent met de Overeenkomst van Parijs.

Aanbevelingen voor verder onderzoek

Relocatie van industrie komt vaak voor tussen de Chinese provincies. Dit geldt vooral voor de maakindustrie, die zich vaak verplaatst van de ontwikkelde naar minder ontwikkelde provincies in China. Dit fenomeen is een bijproduct van de economische ontwikkeling. In principe zou dit kunnen leiden tot een geoptimaliseerde ruimtelijke verdeling van industriële productie. Gegeven de sterke verschillen in emissie-intensiteit tussen vergelijkbare industriële sectoren in verschillende provincies, is het echter interessant om de invloed van verplaatsing van industriële productie op de CO_2 emissies van de industriële sector als geheel te onderzoeken.

Op dit moment worden er verschillende emissiefactoren voor fossiele brandstoffen gehanteerd (b.v. in termen van CO_2 per eenheid calorische waarde). Zowel het het IPCC als de Chinese National Development and Reform Comission hebben (eigen) data sets gepubliceerd. Zulke emissiecoëfficiënten kunnen een cruciale invloed hebben op het berekenen van de CO_2-uitstoot en de keuze voor de ene of de andere coëfficiënt kan leiden tot een overschatting of onderschatting van de CO_2-uitstoot. Dit beïnvloedt ook het antwoord op de vraag of China zijn emissiedoelstellingen kan bereiken. Een beter inzicht in deze situatie is dus van essentieel belang voor toekomstig onderzoek.

Tot slot moeten de projecties van industriële CO_2-emissies worden geactualiseerd. De meeste eerdere onderzoeken waren niet gebaseerd op de laatst voorhanden gegevens ten aanzien van het energieverbruik in de industriële sector. Daarom is de daling van de CO_2-uitstoot in 2014 en 2015 nog nauwelijks meegenomen als basis voor toekomstige projecties. In diverse beleidsdocumenten die in de afgelopen twee jaar zijn vastgesteld, worden nu strengere doelen gesteld met betrekking tot de industriële energie-intensiteit, de industriële structuur en energiestructuur. Aanbevolen wordt dat daarom de projecties van industriële CO_2-emissies worden geactualiseerd, rekening houdend met zowel de meest recente data ten aanzien van energiegebruik en de meest recente beleidsdoelstellingen.

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Curriculum Vitae

Juan Wang was born in 1989 in Linfen, Shanxi province, China. She graduated from Linfen No.3 Senior High School in 2009. From 2009 to 2013 she majored in Information Management and Information Systems and got her bachelor degree from Nanjing University of Aeronautics and Astronautics. In September 2013, she became a master student at Tianjin University. There her major is Management Science and Engineering and her research topic is Energy economics and Environmental management. After this, she continued her studies in September 2015, in the PhD program of Tianjin University. She joined the Department of Industry Ecology, Institute of Environmental Sciences, Leiden University, in 2017, with the support of China Scholarship Council. Her research focuses on the CO_2 emissions and energy consumption of China's industrial sector, including both the historical and future trajectories.

Publication list

Wang J., Rodrigues J.D.F., Hu M.M., Behrens P., Tukker A. The evolution of Chinese industrial CO_2 emissions 2000-2050: a review and meta-analysis of historical drivers, projections and policy goals. Renewable & Sustainable Energy Reviews (submitted in January, 2019).

Wang J., Hu M.M., Tukker A., Rodrigues J.D.F., 2019. The impact of regional convergence in energy-intensive industries on China's CO_2 emissions and emission goals. Energy economics. 80: 512-523.

Wang J., Hu M.M., Rodrigues J.D.F., 2018. The evolution and driving forces of industrial aggregate energy intensity in China: An extended decomposition analysis. Applied Energy. 228: 2195-2206.

Wang J., Hu M.M., Rodrigues J.D.F., 2018. An empirical spatiotemporal decomposition analysis of carbon intensity in China's industrial sector. Journal of Cleaner Production. 195: 133-144.

Wang J., Zhao T., 2017. Regional energy-environmental performance and investment strategy for China's non-ferrous metals industry: a non-radial DEA based analysis. Journal of Cleaner Production. 163: 187-201.

Wang J., Zhao T., Zhang X.H., 2017. Changes in carbon intensity of China's energy-intensive industries: a combined decomposition and attribution analysis. Natural hazards. 88(3): 1655-1675.

Wang J., Zhao T., Wang Y.N., 2016. How to achieve the 2020 and 2030 emissions targets of China: Evidence from high, mid, and low energy-consumption industrial sub-sectors. Atmospheric Environment. 145: 280-292.

Wang J., Zhao T., Zhang X.H., 2016. Environmental assessment and investment strategies of provincial industrial sector in China - Analysis based on DEA model. Environmental Impact Assessment Review. 60: 156-168.

Wang J., Zhao T., Xu X.S., Zhang X.H., 2016. Exploring the changes in energy-related carbon intensity in China: an extended Divisia index decomposition. Natural Hazards. 501-521.