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

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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 Mt in 2015 to 8127.6 Mt 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.

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 pillar 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 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

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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, 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 lifetime 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 2 reviews the related literature. Section 3 introduces the methods and data set. Section 4 presents the results. Section 5 interprets and discusses those results. Section 6 concludes the paper and provides some policy implications.

2. Literature review

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 <4.5%. Using the gray model, Li et al. (2018) suggested that China will achieve the emissions peak if the GDP was no >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 >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.

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.

3. Methods and data sources

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 socio-economic 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, expressed as the product of four terms: $[\frac{CO_2}{OUT}]_{t,i}$ 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; $[\frac{OUT}{TOT}]_{t,i}$ 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); $[\frac{TOT}{GDP}]_{t}$ 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) 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 (3.5), historical data for all variables in Eq. (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).

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, $[\frac{CO_2}{OUT}]_{t,i}$: 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:

(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

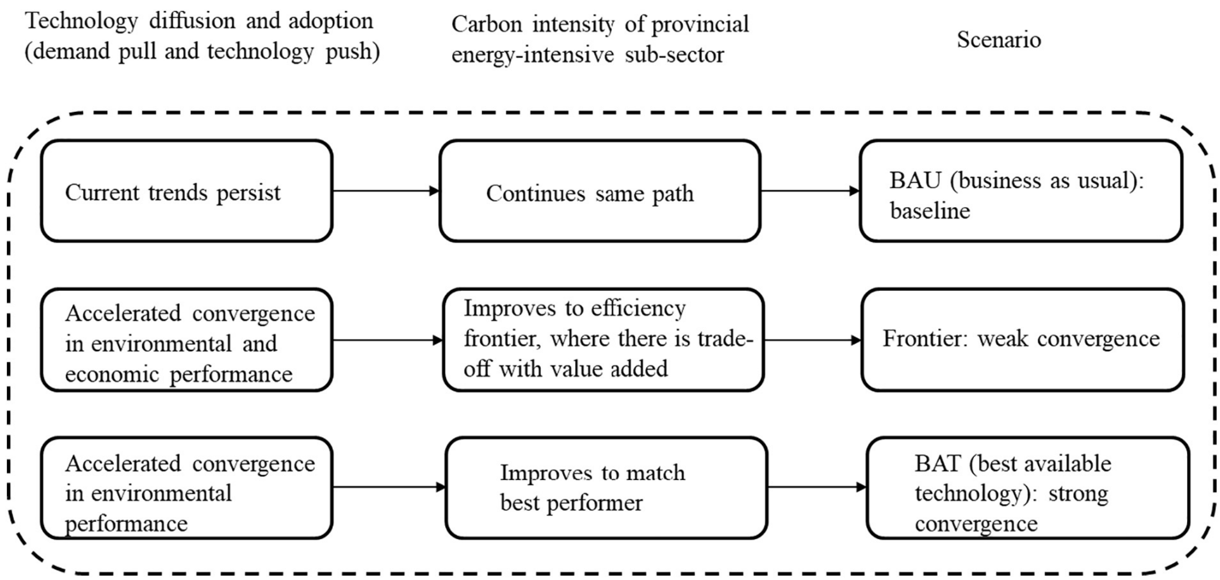

Fig. 1. The framework of scenario design.

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.

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:

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

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 $0 \le \theta \le 1$, 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:

$$\overrightarrow{D_0}(x_k, y_k, b_k; d_y, d_b) = Max\ \beta_k$$

$$\begin{cases} \sum_{j=1}^{J} x_{mj}\lambda_j \le x_{mk} & (m = 1, \dots, M) & (C1) \\ \sum_{j=1}^{J} y_{rj}\lambda_j \ge y_{rk} + \beta y_{rk} & (r = 1, \dots, R) & (C2) \\ \sum_{j=1}^{J} b_{fj}\lambda_j = b_{fk} - \beta b_{fk} & (f = 1, \dots, F) & (C3) \\ \sum_{j=1}^{J} \lambda_j = 1 & (j = 1, \dots, J) & (C4) \end{cases} \tag{6}$$

$$\lambda_j \ge 0 (j = 1, \dots, J), 1 \ge \beta \ge 0$$

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. λ_j are 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) and the undesirable output is CO_2 emissions (Mt CO_2). 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), labor (10^4 people) and energy consumption (million tons coal equivalent); the desirable output vector y contains one indicator, gross output (billion yuan); and the undesirable output vector b contains one indicator, CO_2 emissions (Mt CO_2). The sources of data set are explained in Section 3.5.

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

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

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 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.

3.4. Uncertainty analysis

The model to predict future CO_2 emissions described above (Eqs. (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 $P(X \le x_L) = (100-z)/2\%$ and $P(X \le x_U) = (100-(100-z)/2)\ \%$. 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.

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 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), labor (10^4 people) and energy consumption (Mtce (million tons coal equivalent)); one desirable output, gross output (billion yuan); and one undesirable output, CO_2 emissions (Mt). The capital stock[1] 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 values 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 populations 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.

[1] The capital stock from 2001 to 2015 in this paper is calculated using the perpetual inventory method as $K_t = K_{t-1} * (1-\delta_t)\ \ I_t/P_t$. 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.

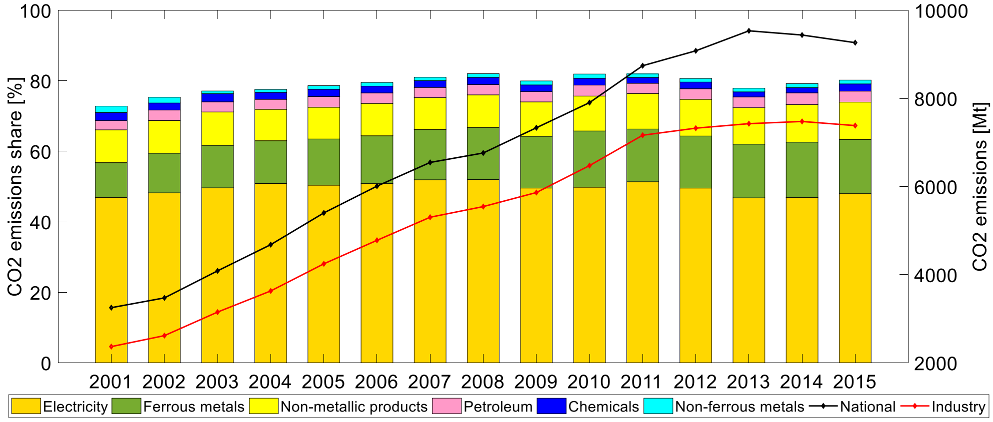

Fig. 2. Historical CO_2 emissions of energy-intensive industries from 2001 to 2015 (Industry = Energy-intensive industries). Bars indicate the contribution of energy-intensive sub-sectors to national total emissions (unit: %); the black line indicates national total emissions and the red line indicates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

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.

4.1. 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 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 Mt, 203 Mt, 53.7 Mt, 37 Mt, 14.6 Mt and 10.7 Mt during the study period, respectively, while emissions from the smallest provinces were <1 Mt except for the electricity sector (12.5 Mt). 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.

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 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,

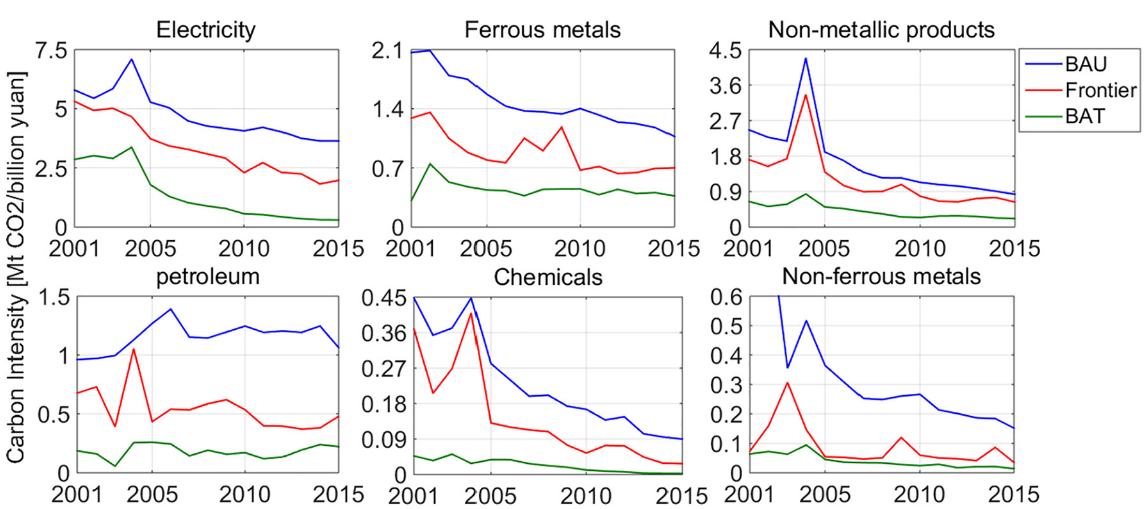

Fig. 3. Historical output-based carbon intensity of each energy-intensive sector. BAU is the historical average carbon intensity of the sub-sector in China. BAT is the historical carbon intensity in the province where the sub-sector performed best. Frontier reflects the carbon intensity of the sub-sector in frontier provinces as defined in Section 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.

Table 1
Future CO_2 emissions of energy-intensive industries under different scenarios (Unit: Mt). BAU means business as usual and BAT is the best available technology scenario.

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

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.

4.2. Assessment of regional convergence on CO_2 emissions

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 Mt. in 2015 to 8127.6 Mt 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 Mt. 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.

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 Mt in 2016 to 6892.9 Mt 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 Mt), followed by the sectors of non-metallic products (737.9–842.3 Mt) and ferrous metals (627.6–920.1 Mt). The remaining three sectors account for no >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

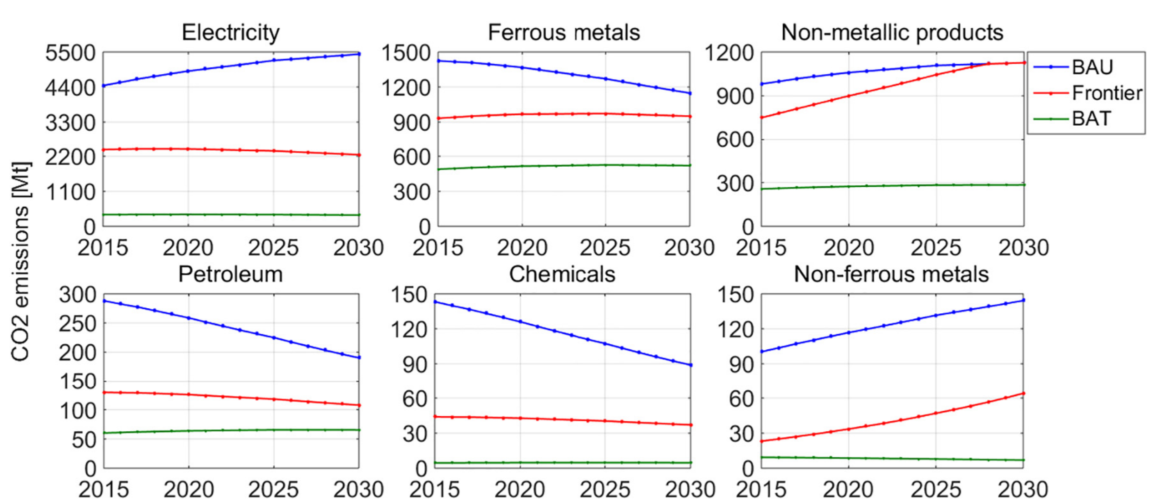

Fig. 4. CO_2 emissions of the six energy-intensive sub-sectors under the three scenarios. BAU means business as usual scenario and BAT is the best available technology scenario. CO_2 emissions of the *non-metallic products* sector in the frontier scenario are higher than those in BAU in the years 2028–2030, 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.

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.

4.3. 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 goals 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.

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. 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 Mt to 157.6 Mt represents 17.8% of the deterministic value of 144.2 Mt, while the sector with the narrowest relative 90%-IQW is non-metallic products, with the range (1070.7–1183.0 Mt) representing 9.8% of the predicted emissions (1148.1 Mt). The relative 90%-IQW of the other sectors lies within these two extremes: the 90%-IQW of the petroleum sector (172.3–201.7 Mt) is 15.4% of the forecast value (190.3 Mt); the 90%-IQW of the electricity sector (5053.5–5828.4 Mt) is 14.3% of 5430.1 Mt; the 90%-IQW of the chemicals sector (81.8–94.0 Mt) is 13.7% of 89.0 Mt; and the 90%-IQW

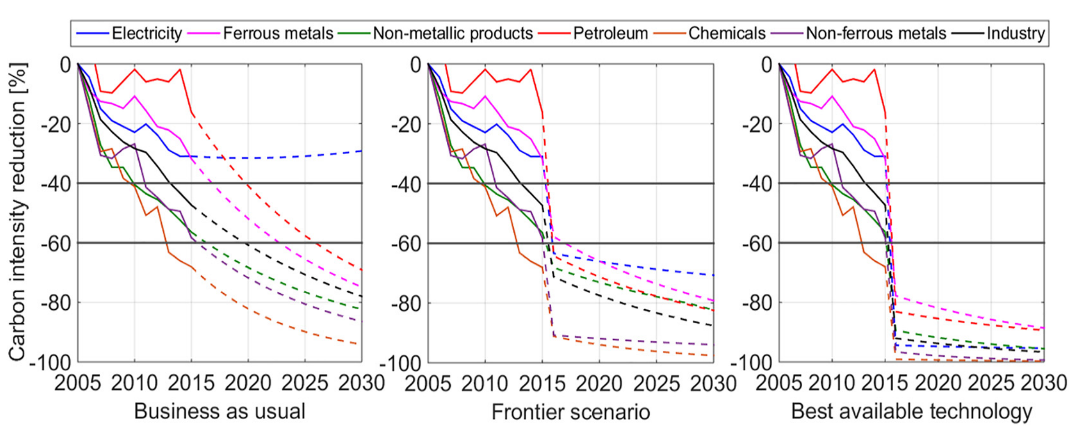

Fig. 5. The contribution of energy-intensive industries to China's emissions goals, measured by carbon intensity reduction (%) relative to BAU-2005, under different regional convergence scenarios. The solid lines are historical data and the dashed lines are forecast data following three scenarios of regional convergence. See Section 3 for the details of each scenario. 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.

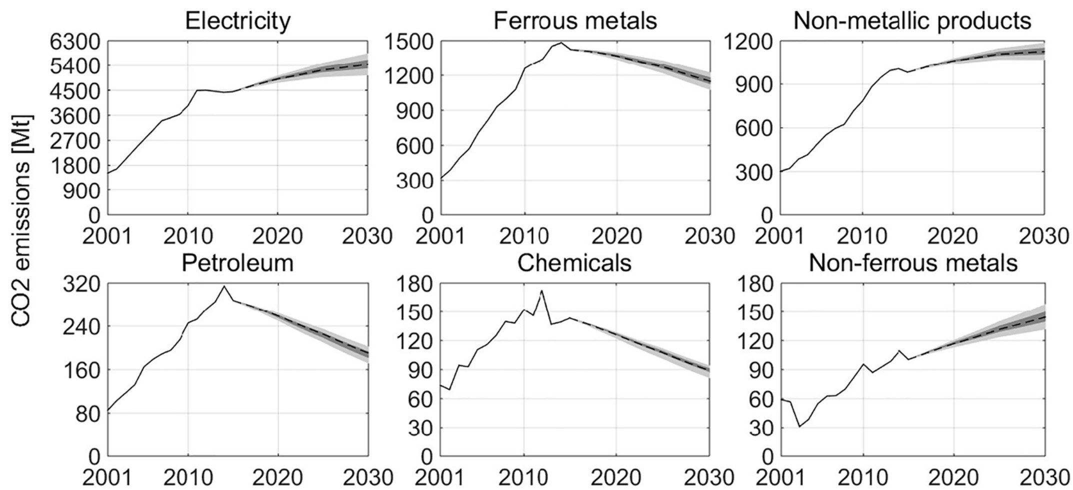

Fig. 6. Uncertainty of the CO_2 emissions forecast under the BAU scenario. The black solid line is historical data, the black dashed line is the deterministic prediction, the dark shaded region is the 50% inter-quantile width and the light shaded region is the 90% inter-quantile width.

of the ferrous metals sector (1078.8–1222 Mt) is 12.5% of 1148.1 Mt. 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.

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, 2002-2016b; 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.

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 >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.

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Supplementary information and data

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