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The evolution of Chinese industrial CO_2 emissions 2000–2050: A review and meta-analysis of historical drivers, projections and policy goals

Juan Wang [a,b,*], João F.D. Rodrigues [a], Mingming Hu [a,c], Paul Behrens [a,d], Arnold Tukker [a,e]

[a] Institute of Environmental Sciences (CML), Leiden University, Einsteinweg 2, 2333 CC, Leiden, the Netherlands
[b] School of Finance, Tianjin University of Finance and Economics, Tianjin, 300222, China
[c] School of Construction Management and Real Estate, Chongqing University, Chongqing, 400045, China
[d] Leiden University College the Hague, 2595 DG, The Hague, the Netherlands
[e] Netherlands Organization for Applied Scientific Research TNO, Anna van Buerenplein 1, 2595 DA, The Hague, the Netherlands

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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. This study reports a literature survey that quantitatively describes the evolution of these emissions from 2000 to 2050 in the context of policy goals. The 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 industrial sub-sectors, with *ferrous metals* and *non-metallic products* sectors 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.

1. Introduction

Global industrial and electrical emissions have increased by an average of 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 aims for a reduction in industrial carbon and energy intensity 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 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. This study here presents the first systematic review and meta-analysis on such drivers and trajectories. This study also includes a review of policy targets, and indicates whether these targets may be met with reference to the studies reviewed. This paper first presents the survey method (Section 2), then analyzes drivers of emissions (Section 3), projections

* Corresponding author. Institute of Environmental Sciences (CML), Leiden University, Einsteinweg 2, 2333 CC, Leiden, the Netherlands.
E-mail address: j.wang@cml.leidenuniv.nl (J. Wang).

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(Section 4), and policies (Section 5). The findings are discussed in Section 6, while Section 7 concludes.

2. Method

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

This results in a final selection of 135 papers, including 65 on drivers and 70 on future trajectories. This study performs 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 are excluded from the meta-analyses because they do not report numerical data. These future trajectories are compared 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), Renewable & Sustainable Energy Reviews (15 papers), Applied Energy (15 papers) and Energy (13 papers). Table A1 of SI (Supplementary Information) presents the details of the top-10 most-cited papers.

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

This paper first discusses the spatial (Section 3.1) and sub-sectoral (Section 3.2) distribution of historical industrial emissions. To provide an overall perspective, CO_2 emissions inventories calculated using the IPCC Sectoral Emission Accounting approach were collected from the China Emission Accounts and Datasets (CEADs). Under the IPCC Sectoral Emission Accounting approach, emissions are calculated as the product of fossil fuel consumption volumes and respective emission coefficients for each fuel type, with the latter in turn calculated as the product of CO_2 emissions per net caloric value, net caloric value and oxidation ratio. The process-emissions of cement were included in this paper and allocated to the *non-metallic products* sub-sector. National emissions increased from 3 Gt to 9.5 Gt between 2000 and 2013, and then decreased slightly in 2014 (9.4 Gt) and 2015 (9.3 Gt). Industrial emissions also declined in 2014 and 2015, while emissions of other sectors such as agriculture, transportation, service and households increased throughout. Section 3.3 reviews studies of historical drivers. Section 3.4 concludes in analyzing the contribution of common drivers to changes in CO_2 emissions across time.

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 [6]. As shown in Fig. 2, most provinces saw increased emissions from 2000 to 2015. The top three emitters, all of which were regions of major industries, were Shandong, Jiangsu and Hebei. The second group included 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.

China's industrial carbon intensity, which is CO_2 emissions per unit of industrial value added (IVA), decreased from 0.61 to 0.45 Mt/billion yuan from 2000 to 2015 (industrial value added, 2000 constant prices, NBSC [7]). The central and northwestern provinces had higher emission intensities, whereas eastern coastal areas had lower intensities (see Fig. 2). The industrial carbon intensity of Xinjiang, Ningxia, Shanxi and Gansu was 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 [8].

Along with spatial variations in industrial emissions there was a large variation across sub-sectors, mainly due to China's ongoing industrialization and urbanization [9,10]. The *electricity* sub-sector saw the largest increasing emissions 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.

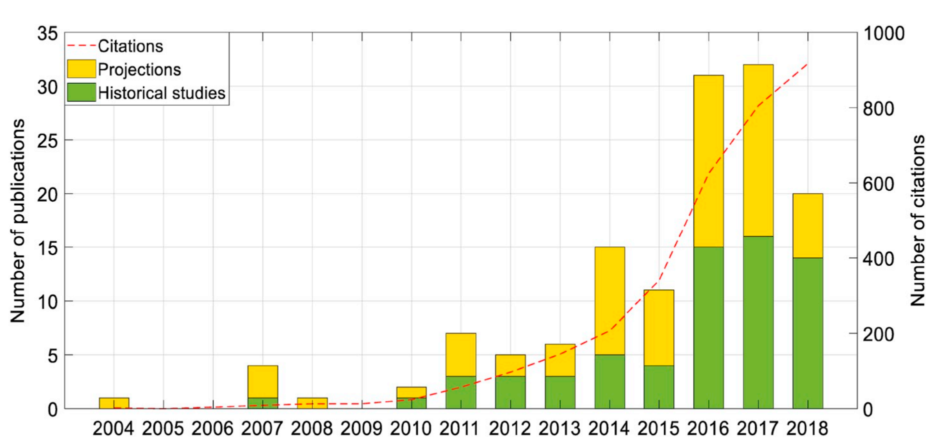

Fig. 1. Number of publications and citations in time series (status on 27 November 2018).

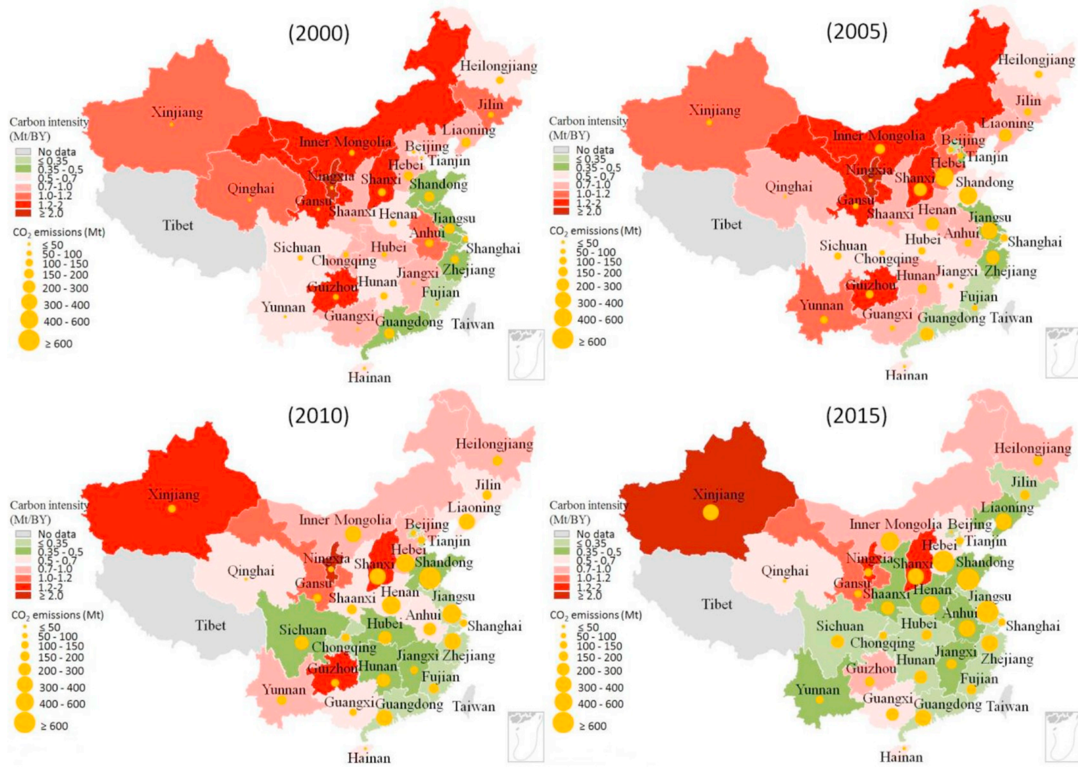

Fig. 2. The trajectories of CO_2 emissions and carbon intensity from spatial perspective. Sources: CO_2 emissions are from the China Emission Accounts and Datasets (CEADs) and carbon intensity (CO_2 emissions per unit of industrial value added) is from the authors' calculation. Industrial value added has been converted to 2000 constant price (authors' calculation).

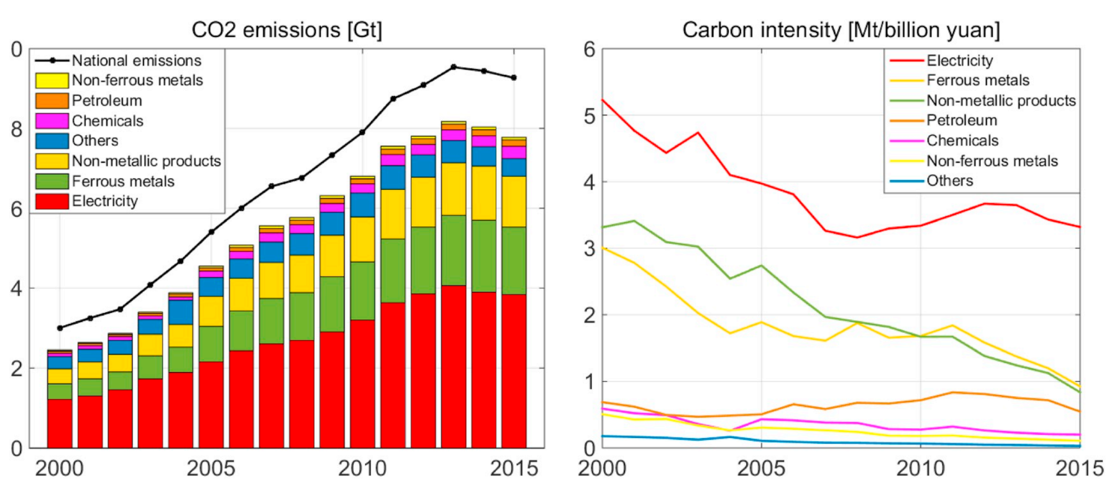

Fig. 3. The trajectories of CO_2 emissions and carbon intensity at sector level. Sources: CO_2 emissions are from the China Emission Accounts and Datasets (CEADs) website and carbon intensity is CO_2 emissions per unit of industrial value added (authors' calculation). Industrial value added has been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

3.2. *Analysis of driving forces*

The emission drivers and general findings across the literature are summarized in Tables 1–3 (for further details see Tables A3–4). Studies employing index decomposition analysis and econometric method across the literature are reviewed and presented. The drivers analyzed include energy intensity, industrial activity and 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).

Across all studies (see Table 1), industrial activity drove emission 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 all 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 (index decomposition analysis) and econometric studies are often different, there are some general findings across studies. On a province

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. [11]	C ↑	1998–2005	IDA	–	*–	*+	+	–		5
Chen et al. [12]	C ↑	1986–2007	IDA		*–	*+	+	+	v	5
Xu et al. [13]	C ↑	1996–2011	IDA	–	*–	*+	+	+	v	5
Liu et al. [14]	CI ↓	1996–2012	IDA	+	*–			–		3
Ouyang and Lin [15]	C ↑	1991–2010	IDA	–	*–	*+	–		v	5
Xu et al. [16]	C ↑	1995–2012	IDA		*–	*+	+	–	v	4
Zhao et al. [17]	C ↑	1993–2013	IDA	–	*–		–		v	7
Wang and Feng [18]	C ↑	2000–2015	IDA & PDA		*–	*+	+		v	7
Zhao et al. [19]	C ↑	1992–2012	IDA	–	*–	*+		+	v	5
Jiang et al. [20]	C ↑	2000–2014	IDA	–	*–	+	–			4
Wang et al. [21]	CI ↓	2006–2014	IDA & PDA	–	*–		+		v	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 (C/Energy), energy intensity (Energy/IVA), industrial activity (IVA), energy mix (the shares of energy types in total consumption), industrial structure (the shares of IVA of different sub-sectors in total) 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 "↓" 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 "*".

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. [22]	$C^{\#}$ ↑	9 regions	2005–2009	IDA	–	7–,2+	+	7+,2–	+		5
Zhou et al. [23]	$C^{\#}$ ↑	8 regions	1996–2012	IDA	4+,4–	7–,1+	7+,1–	5–,3+	+		5
Wang et al. [24]	$CI^{\#}$28↓ 2↑	30 provinces	1999–2015	IDA	20–,10+	29–, 1+		12–,18+			3
Wang and Feng [25]	$C^{\#}$29↑ 1↓	30 provinces	2000–2015	IDA		30 *–	30 *+	14–,15+		v	6
Zhao et al. [26]	C ↑	Shanghai	1996–2007	IDA	–	*-	*+		–		4
Shao et al. [27]	C ↑	Shanghai	1994–2009	IDA			+		–	v	3
Yang and Chen [28]	C ↑	Chongqing	2004–2008	IDA		–	*+	+	+		4
Deng et al. [29]	C ↑	Yunnan	1997–2012	IDA & SDA		*-	*+	–	+	v	7
Liu et al. [30]	C ↑	Henan	2001–2012	IDA		–	*+	+	*-		4
Shao et al. [31]	C ↑	Shanghai	1994–2011	IDA		–	*+	+	*-	v	7
Wu et al. [32]	C ↑	Inner Mongolia	2003–2012	IDA		–	*+	+	+	v	5
Zhang et al. [33]	CI ↓	Xinjiang	2000–2014	IDA		–		+	*+		3
Jia et al. [34]	C ↑	Nanchang	1998–2014	IDA		*–	*+	–	–	v	5
Zhao and Li [35]	C ↑	Guangdong	2000–2014	IDA		–	*+	+			3
Kang et al. [36]	C ↑	Tianjin	2001–2009	IDA	+	–	*+	+	+		5
					GDP (IVA)	IIS	P	Urb	FEM	Others	Tot
Wu et al. [37]	C	Inner Mongolia	2010–2012	Econometrics	+	–	+	+		v	5
Wu et al. [38]	C	Inner Mongolia	2011	Econometrics	+	+	+	+		v	6
Xu et al. [39]	C	Yangtze River Delta	2000–2014	Econometrics	+	–			+	v	12
Lin and Xu [40]	C^{II}	Shanghai	1960–2015	Econometrics	+,–	+,–		–,+	+, -	v	5

Note: See caption for Table 1 for definitions of all terms except whereSDA, *P*, *Urb*, *IIS* and *FEM* refers to structure decomposition analysis, 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.

level the key drivers were industrial activity (IVA) 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 emission coefficient, energy intensity, industrial activity, energy mix and industrial structure across regions and provinces. For example, the shift in industrial structure instead of energy intensity was the major driver contributing to the decrease in industrial emissions for Shanghai and Henan.

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 was no unanimous finding for whether energy or industrial structure was emission driver 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 changed 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).

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

The results reported 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. [11]; Chen et al. [12]; Ren et al. [41]; Xu et al. [13]; Ouyang and

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. [41]	C↑	Manufacturing	1996–2010	IDA	–	*–	*+	+	–			5
Wang et al. [42]	C↑	Energy-intensive industris	2000–2007	IDA	–	*–	*+	+				5
Wang et al. [43]	CI↓	Energy-intensive industris	1996–2014	IDA	+	*–			–			3
Jiang et al. [44]	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. [45]	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. [46]	C↑	Electricity	1995–2014	IDA		*–	*+	–	+		v	10
Li et al. [47]	C↑	Electricity	1990–2013	IDA	–	*+	+				v	7
Zhou et al. [48]	C↑	Electricity	2004–2010	IDA	+	*–	*+	–	+			5
Liu et al. [49]	ECI↓	Electricity	2000–2014	IDA		*–		–			v	4
Peng and Tao [50]	ECI↓	Electricity	1980–2014	IDA		*–					v	2
Wang et al. [51]	ECI↓	Electricity	1995–2014	IDA		*–		+			v	4
Yan et al. [52]	$C^{\#}28\uparrow 2\downarrow$	Electricity	2000–2013	IDA	Almost –	13–,17+	+					3
Sun et al. [53]	C↑	Ferrous metals	1980–2008	IDA	–	*–	*+	+				4
Lin and Zhang [54]	C↑	Non-metallic product	1991–2010	IDA	–	*–	+	–	–			5
Wang et al. [55]	C↑	Non-metallic product	2005–2009	IDA	–	*–	*+	+				4
Ren and Hu [56]	C↑	Non-ferrous metals	1996–2008	IDA	–	*	*+	+				4
Shi and Zhao [57]	C↑	Non-ferrous metals	2000–2011	IDA	–	*–	+	–				4
Fan et al. [58]	C↑	Petrochemicals	2000–2010	IDA			+		–		v	3
Lin and Long [59]	C↑	Chemical	1981–2011	IDA		*–	*+	–			v	4
					GDP per capita	EI	Urb	Ind	FEM	P	Others	Tot
Lin et al. [60]	C	Manufacturing	1980–2012	Econometrics	+						v	3
Xu and Lin [61]	C^{III}	Manufacturing	1980–2014	Econometrics	–,+,–	+,+,–	–,+,+	–,–,+	–,–,+			5
Xu and Lin [62]	C	Manufacturing	2000–2013	Econometrics	+	+	+	+	–	+		6
Lin and Xu [63]	C	Manufacturing	2001–2015	Econometrics	+	+	+	+	–	+		6
Xu et al. [64]	C	Manufacturing	2000–2015	Econometrics	+		+	+	–	+	v	6
Xu and Lin [65]	C	Manufacturing	2000–2014	S-Econometrics	+	+	+	+	–	+		6
Wang et al. [66]	C	Manufacturing	2000–2013	S-Econometrics	+	+	+					3
	C	Electricity	2000–2013	S-Econometrics	+	+	+					
Zhao et al. [67]	C	Electricity	1980–2010	Econometrics	+						v	3
Yan et al. [68]	C	Electricity	1990–2014	S-Econometrics	+	+	+	+		+	v	8
Wen et al. [69]	C	Electricity	2000–2014	Econometrics	+		+	+			v	5
Yu et al. [70]	CI	Ferrous metals	1990–2010	Econometrics	+						v	3
Xu and Lin [71]	C	Ferrous metals	2000–2013	Econometrics	+	+	+	+	–			5
Xu and Lin [72]	C^{II}	Ferrous metals	1980–2013	Econometrics	+,–	–,+	+,–	–,+	+,–			5
Xu and Lin [73]	C	Ferrous metals	2000–2013	Econometrics	+	+	+	+	+			5
Xu et al. [74]	C	Ferrous metals	2000–2015	Econometrics	+	+	+	+	+	+		6

Note: See Tables 1 and 2 for notes on the meaning of symbols except ECI, S-Econometrics and C^{III}. ECI is the carbon intensity of electricity generation in *electricity* sector. 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. C^{III} refers to studies where short, medium and long-term relationships between emissions and drivers were explored.

Lin [15]; Xu et al. [16]; Zhao et al. [17]; Wang and Feng [18]; Wang and Feng [25]). This paper extracted these data and showed the drivers over time across the different studies (see Fig. 4).

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. Since 2012, one of the drivers for decreasing emissions appears to be the energy mix, likely due to fuel switching. There is evidence that the ratio of coal in the industrial sector peaked at 65% in 2010 and decreased to 59% in 2015 (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. There was little change in proportion of oil consumption during period of 2012–2015, while the consumption of natural gas increased from 3.0% to 3.4% [2]. The large-scale deployment of renewables in recent years will likely lead to further long-term emission reductions. Nationally, the proportion of thermal power generation has declined from 78% in 2013 to 74% in 2015 [2]. The decrease in the dependence on coal, and its replacement by lower emission energy carriers such as natural gas, contributed to the decrease in industrial emissions since 2012. From Fig. 4, it can be seen that the industrial structure had mixed impacts on emissions before 2007, but afterwards it began to drive emission decreases. This phenomenon can be explained by the transition of industrial structure from energy-intensive to high-tech sectors over the

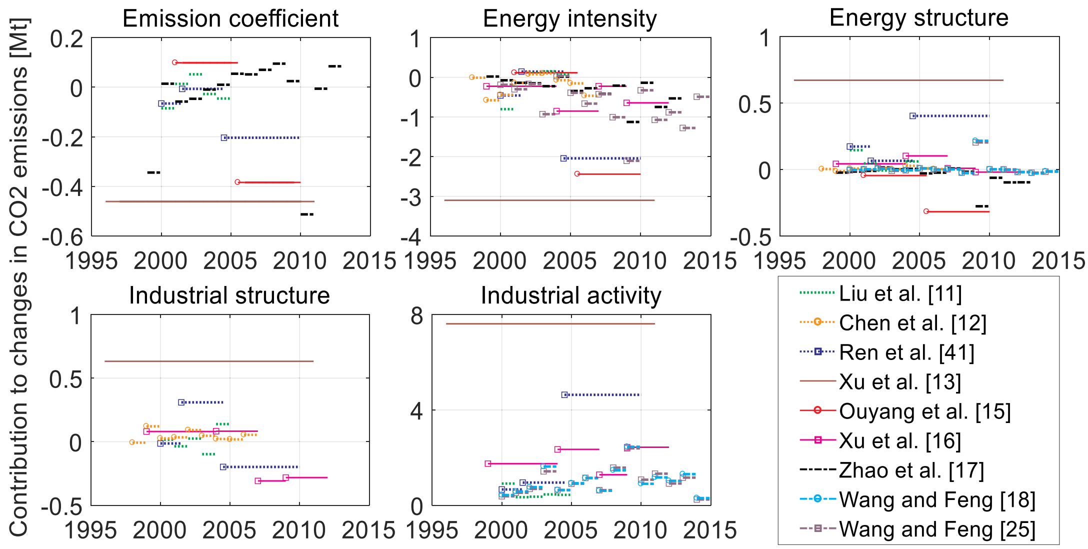

Fig. 4. Contribution of drivers to total industrial emissions. Note: The results of Ren et al. [41], Xu et al. [13], Ouyang et al. [15] and Xu et al. [16] were multi-year results, others were single-year results.

period. A key indicator is the proportion of IVA of energy-intensive industries such as *petroleum*, *ferrous metals* and *electricity generation* in total, which overall decreased by 4.1%. High value-added industries increased by 6.4% from 2007 to 2015 [7]. Emission declines also can be attributed to decreasing energy intensity (after 2005), where energy intensity decreased by 22% from 2005 to 2015. Meanwhile, the energy intensity in most industrial sub-sectors and provinces also declined [2,7]. In addition, the growth of IVA in 2013–2015 was somewhat slower than in previous years [7], but still acted as the dominant factor driving emissions. These indicators strongly suggest that the decrease in industrial emissions since 2013 can be attributed to the transition in energy and industrial structure, along with a decrease in energy intensity.

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

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 this study performs 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 data) models. Top-down models have fewer technological details, but yield a more complete

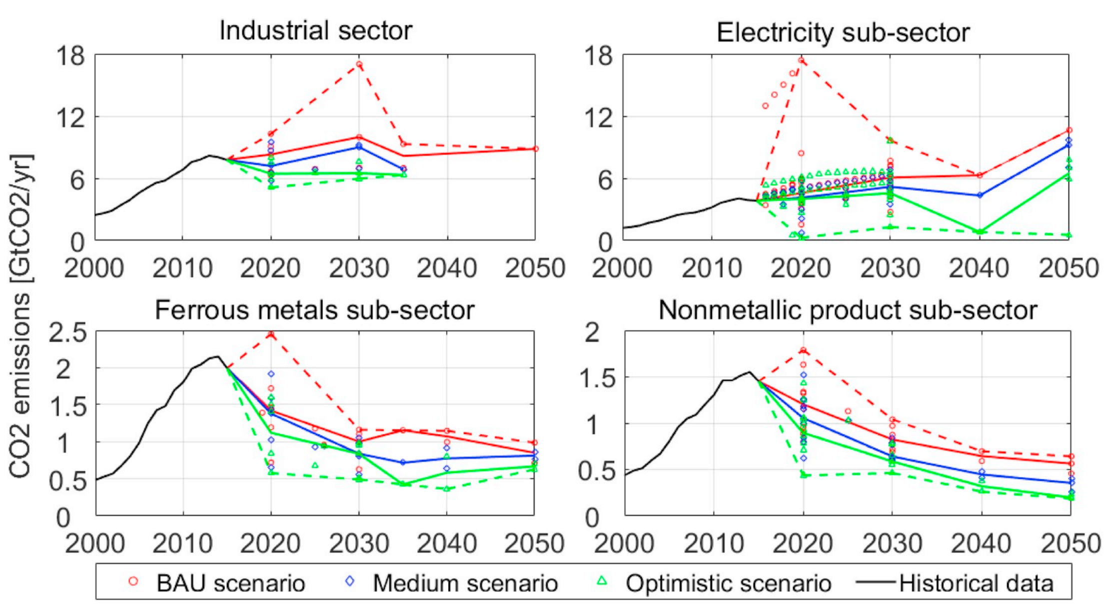

Fig. 5. Projections of CO_2 emissions in industrial sector and its major sub-sectors. The red and green dashed lines show the maximum and minimum values, respectively. The red, blue and green solid lines reflect median emissions under BAU, medium and optimistic scenarios, respectively. The median emissions are obtained in the following way: (1) The emission projections of reviewed studies in different scenarios are extracted; (2) The median of the extracted data in each scenario is considered as median emissions. 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. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

representation of the wider economy [75]. 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). The scenario assumptions were harmonized across the papers to obtain three scenarios: BAU (business-*as*-usual), medium and optimistic. If more than two scenarios were reported, the one exhibiting highest emissions is considered as BAU scenario and the one exhibiting lowest emissions is considered as the optimistic scenario. Emissions in the medium scenario is obtained as the median over all other reported scenarios. If only two scenarios were reported in the original study, only a BAU and optimistic scenario are considered in the meta-analysis.

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 $GtCO_2$, depending on the scenario considered (see Fig. 5): the BAU scenario spans a range of 7–17 $GtCO_2$; the medium scenario 6.5–9 $GtCO_2$; and the optimistic scenario 6–6.9 $GtCO_2$. Median estimates in the BAU and medium scenarios generally reach an emissions peak in 2030 at 10 $GtCO_2$ and 9 $GtCO_2$, respectively, while the median estimates for the optimistic scenario display a downtrend from 2015 to 2020 and 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 $GtCO_2$ in 2050 (see Fig. 5). Less available data in 2040 and 2050 limits the analysis to ranges in 2030: the BAU scenario spans 2.8–7.7 $GtCO_2$; the medium scenario 3.5–6.9 $GtCO_2$; and the optimistic scenario 1.3–6.6 $GtCO_2$. 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. [76] combined the GM (1,1) model (a model for prediction using Gray System Theory), an autoregressive integrated moving average model and a second order polynomial regression model together to forecast the CO_2 emissions from thermal power generation. The result indicated that CO_2 emissions will be 17.4 Gt in 2020. Herein, the CO_2 emissions of electricity sector are much higher than total industrial emissions in 2020. Tracking the historical CO_2 emissions reported in this paper, it can be found that the estimates of emissions from the *electricity* sector were 5.1 Gt in 2005 and almost 7 Gt in 2010, which were much higher than the official data (2.2 Gt in 2005 and 3.8 Gt in 2010) as well as the industrial total emissions (4.2 Gt in 2005 and 6.3 Gt in 2010). On the lower end, Kroeze et al. [77] obtained a much lower projection (1.6 Gt, 0.72 Gt and 0.26 Gt 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 $GtCO_2$ to 1 $GtCO_2$. Regarding each scenario, the ranges are 0.77–1 $GtCO_2$ in the BAU, 0.7–0.85 $GtCO_2$ in the medium and 0.63–0.71 $GtCO_2$ 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 [78]. 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 span 0.19–0.56 $GtCO_2$, as shown in Fig. 5: the BAU scenario spans 0.46–0.64 $GtCO_2$; the medium scenario 0.26–0.40 $GtCO_2$; and the optimistic scenario 0.19–0.24 $GtCO_2$. The median emissions show a downtrend from 2015 to 2050, at which point these three scenarios exhibit values of 0.56 $GtCO_2$, 0.35 $GtCO_2$ and 0.2 $GtCO_2$, respectively.

The projections of CO_2 emissions in the sectors of *chemical*, *petroleum*, *nonferrous metals* and energy-intensive industries are shown in Table 4.

Table 4
The projections of CO_2 emissions from energy-intensive industries, *chemical*, *petroleum*, and *nonferrous metals* sectors (unit: $GtCO_2$).

Sector	Scenarios	2020	2030	References
Chemicals	BAU	1.2	–	Lin and Long [79]
	Medium scenario	0.99	–	
	Optimistic scenario	0.84	–	
Petroleum	BAU	0.53	0.94	Xie et al. [80]
	Medium scenario	0.52	0.92	
	Optimistic scenario		0.9	
Non-ferrous metals	BAU	0.43	–	Wen and Li [81]
	Medium scenario	0.4	–	
	Optimistic scenario	0.4	–	
	BAU	0.28	0.28	Li et al. [82]
	Optimistic scenario	0.28	0.32	
Energy-intensive industries	BAU	11.5	23.6	Lin and Tan [83]
	Medium scenario	9.5	14.3	
	Optimistic scenario	8.2	9.5	
	BAU	7.5 (2026-peak)		Li et al. [84]
	Medium scenario	7.1 (2024-peak)		
	Optimistic scenario	6.9 (2022-peak)		

The CO_2 emissions of the *chemical process* sector are estimated to increase to 1.2 $GtCO_2$, 0.99 $GtCO_2$ and 0.84 $GtCO_2$ in 2020 in three scenarios, respectively [79]. By 2030, the emissions of the *petroleum* sector in three scenarios will respectively increase to 0.94 $GtCO_2$, 0.92 $GtCO_2$ and 0.9 $GtCO_2$ [80]. The CO_2 emissions of the *non-ferrous metals* sector span 0.28–0.43 $GtCO_2$ in 2020, which are around those in 2015 (0.39 $GtCO_2$) [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 $GtCO_2$, 14.3 $GtCO_2$ and 9.5 $GtCO_2$ in 2030 under the three scenarios [83]. However, Li et al. [84] 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 $GtCO_2$.

4.3. Scenario assumptions of lowest emissions

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

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 scenario. Other studies assume that energy intensity decreases faster than under BAU.

Optimistic assumptions within the *electricity* sector focus mainly on the energy intensity and energy mix. For example, some studies assume power plants have a higher efficiency than under BAU, while others assume that old and 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] assumes 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. Policies

The Chinese Government has a tradition of frequent and strong top-down policy measures. This section analyzes the policies concerning climate change, energy conservation, industrial structure and energy mix enacted since 2001. As indicated in Section 2, policy targets set by various Chinese authorities are reviewed. They are listed in Tables A9–12 of SI. This section will 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, these are covered next.

The number of recent targets for each item 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 industrial carbon intensity was set by 2020 and 2025, respectively. The industrial energy intensity target is an 18% reduction by 2020 and 34% by 2025. Concerning the transition in industrial structure, energy-intensive industries are 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 an 88% increase in the share of output value is 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 4).

This study 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

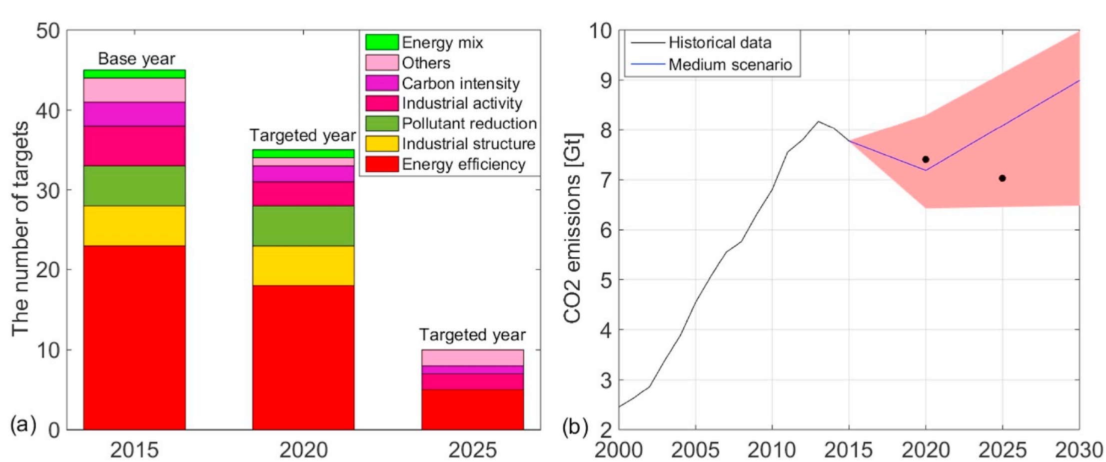

Fig. 6. (a). The number of targets for carbon-related indicators in industrial sector. (b). Comparison between targeted industrial emissions and the median emissions extracted from previous studies in three scenarios. Note: The solid black dots are the targeted industrial emissions in 2020 and 2025. 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 the 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.

reviewed in Section 4. To obtain the absolute emissions corresponding to the carbon intensity reduction targets, the historical average growth rate of the share of IVA in GDP over the past twelve years as well as future projections of GDP are used (see Table A13). The projection of the share of IVA was obtained from the authors' calculation and China's future GDP was obtained from the World Bank [85]. From this estimate, it can be found emissions of 7.4 Gt in 2020 and 7 Gt 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.

6. Discussion

In this study, three separate bodies of literature have been reviewed: historical drivers, projections and policy goals. This section now discusses how these separate threads interact, the robustness of predictions, factors driving the uncertainty of historical studies and concludes 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 three major factors for this decrease (detailed discussion, see Section 3.3).

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 emission reduction, are regulated by recent policies with future targets (as discussed in Section 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.

CO_2 emission projections in BAU scenario from the meta-analysis are compared 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 $GtCO_2$ [1]. IEA and EIA (Energy Information Administration) projections of energy-related CO_2 emissions give 10.6 $GtCO_2$ and 10.4 $GtCO_2$, respectively [3,86]. Grubb et al. [75] reviewed the projections of China's CO_2 emissions up to 2030, indicating that BAU scenario has a range of 12–18 $GtCO_2$. The meta-analysis in the current study yields industrial median emissions of 10 $GtCO_2$, which is within the potential national emissions estimated above. There is a close agreement between median emissions from the meta-analysis and international estimates. For the *electricity* sector, median emissions of the meta-analysis in the BAU case is 5.9 $GtCO_2$ by 2030, which is well consistent with IEA's report (5.5 $GtCO_2$). 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 this paper reviewed calculates emissions themselves. The IPCC Sectoral Accounting approach is commonly used. According to the calculation framework of IPCC, 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 emission 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. [87] and Liu et al. [88] considered coal consumption only. Akashi et al. [89] considered coal, oil, natural gas, biomass and electricity, while Zhou et al. [90] considered coal, electricity, liquids, gases and biomass. Uncertainties arising from energy consumption statistics also play a part in many other studies [75,91–101]. 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 [102,103]. 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 [2,104]. Shan et al. [105] pointed out that there are large differences in the data published by IPCC and NDRC. Herein the IPCC data is commonly used by papers reviewed in this study. 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 [106]. Other than the historical 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 carbon 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 CO_2/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.

7. Conclusion and policy implications

The industrial sector in China accounts for 68% of energy consumption and 84% of CO_2 emissions. This study 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 structure 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° above pre-industrial levels and a more ambitious target of 1.5°. 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 the results of 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 industrial 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 [107,108].

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Appendix A. Supplementary data

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