The effects of structural and technical change on China's industrial CO_2 emissions pathways under uncertainty

Abstract

The industrialization process in China has resulted in the fast growth of the country's energy consumption and CO_2 emissions. Examining the effects of industrial structural change on the emissions pathways in the mid-term future would help advance understanding of how industrial policy choices affect the fulfillment of the strategic climate targets of emissions peaking and carbon neutrality. This study couples index decomposition analysis (IDA) with an additive nonparametric regression model to project the possible emissions pathways with different industrial structures. A set of scenarios are developed following the storylines of shared socioeconomic pathways (SSPs) to examine these effects in an uncertain environment towards 2040. The results show that structural change has played an increasing role in curbing carbon emissions of China's industrial sectors since 2000. The emissions reductions attributable to this effect were 686 million tons (Mton) between 2000 and 2013, and these contributions to emissions mitigation rose to 798 Mton between 2014 and 2019. The scenario results suggest that the aggregated effect of energy efficiency and structure upgrade will decrease emissions by 43% in 2040 relative to the level in 2019 in the ideal case. Regardless of the uncertainties in scenario settings, heavy industries will continue to dominate China's industrial emissions through 2040. Nevertheless, a significant structural change with the increased share of high-tech industries, e.g., information and communication technology, could lead to more than 30% reduction in emissions compared to the case with minor change.

Key Policy Insights

- A rapid expansion of heavy industry was the primary factor driving the rapid growth of China's industrial CO_2 emissions since 2000. Industrial structural change is the second most significant factor curbing emissions growth, and the influence of this factor is increasing.

- Keeping up the momentum of structural change and technological upgrades in the industrial sector would make it possible for industry emissions to decrease in the mid-term future, therefore contributing substantially to the China's goal of peaking emissions by 2030.
- Realizing carbon neutrality in the longer term needs not only structural change in industry but also a fundamental transformation of the energy supply system.

Keywords

Industrial CO_2 emissions; structural change; nonparametric additive model; decomposition analysis; uncertainty

1. Introduction

China has pledged to peak its CO_2 emissions by 2030 and strive to realize carbon neutrality by 2060. Realizing the goals indicates a fundamental transition in every aspect of the economy. A large body of studies has examined the driving factors behind the rapid increase in China's CO_2 emissions in the past decades (Fatima et al., 2019; Zhang et al., 2019). Since the early 2000s, China's fast economic growth features rapid expansion of heavy industries, such as iron and steel making, cement production, chemicals production, among others, resulting in rapid increases in fossil fuel consumption and CO_2 emissions. In more recent years, a structural change has been taking place as high-tech industries, such as information and communications technology, are emerging and burgeoning, and the expansion of heavy industries seemingly is coming to a halt.

Some studies observe that a clear structural break in China's emission pattern around 2015 is led by industrial structure upgrades and energy system transitions between 2013 and 2016; it is believed that this decline is structural and likely to be sustained if the nascent industrial and energy system transitions continue (Guan et al., 2018; Zheng et al., 2019). However, the latest data of energy statistics and CO_2 emissions estimates appear to contradict the optimistic conclusion, implying that the structural change faces a highly uncertain environment. This structural change, compounded with other factors such as energy efficiency and clean energy development, would significantly affect the overall emissions profiles. As China enters the post-industrialization era, decoupling emissions from economic growth necessitates a continued upgrading of the industrial structure. Therefore, a deep understanding of how this effect would unfold in an uncertain future is crucial to policy-making, notably to development of emissions mitigation strategies and sustainable industrial development.

The industry sector accounts for approximately two-thirds of China's total energy use and carbon emissions (China National Bureau of Statistics, 2021). In the near-term future, it is expected that emissions from the service sector will keep growing, indicating that the emissions of China's industry sector are supposed to decline faster to fulfill the goal of peaking the country's total emissions by 2030. However, uncertain structural change in China's industry sector remains largely unexplored, particularly with respect to emissions mitigation scenarios that examine futures for reaching China's ambitious climate goals.

This study aims to bridge this knowledge gap. It constructs an additive nonparametric regression model coupled with index decomposition analysis (IDA); it is based on the latest energy statistics and emissions data of China's industry sectors from 2000 to 2019 to project the possible emissions pathways with different industrial structures. By the means of the modeling approach, a set of scenarios is developed following the storylines of shared socioeconomic pathways (SSPs) for four divided groups of sub-industry sectors to examine the uncertain effects of structural change on the emissions pathways of China's industry sectors towards 2040.

The remainder of this paper is structured as follows. Section 2 presents a brief summary of the literature and highlights the contributions of this study. Section 3 describes the details of the methodological framework, including the decomposition method, the additive nonparametric regression model, scenario settings, and data collection in this study. Section 4 presents the results of decomposition, regression, and scenario analysis, interprets the effects on the four industry groups as well as the aggregated total and explains the implications of a large variety of emissions pathways under each scenario. Section 5 summarizes the policy implications of the results and concludes with reflections on the need for further research.

2. Literature review

Studies assessing sectoral emissions and the socioeconomic driving forces fall into two categories (Ang and Goh, 2019). One is retrospective analysis focusing on disentangling crucial driving factors behind the historical development of energy consumption and energy-related CO_2 emissions. The other domain, referred to as prospective analysis, aims to extends the method to investigate the development and analysis of future emissions scenarios (Ang, 2015; Ang and Goh, 2019). Traditionally IDA has been used to analyze historical changes in energy consumption or CO_2 emissions. There are a large number of retrospective analysis examples on different regions, sectors, and time scopes, in which structural decomposition analysis (SDA) and IDA are widely adopted (Chen et al., 2013; Ouyang and Lin, 2015; Wang and Feng, 2017; Yu et al., 2015). In fact, an exhaustive overview of these studies would be prohibitive. Some examples in China's industry sectors include power generation, iron & steel production (Xu and Lin, 2016), cement manufacturing (Zhang et al., 2015), etc. Common findings can be drawn from these studies, particularly for those focusing on the rapidly increasing period since 2000. For instance, it is argued that industrial output exerted significant positive impacts on the change in energy use and emissions; however, the negative component in this change could be attributed to energy intensity improvement driven by technology advancement and optimization of capacity scale. The economic effects of carbon emission transfers were also assessed across China's industries or global supply chains (Jiang and Green, 2017; Sun et al., 2017). The prospective analysis deals with emissions scenarios using various IDA-based frameworks and has become a nascent application area (Ang and Goh, 2019). Table S1 in the Supplementary Material (SM) summarizes some basic features of selected studies of this kind. The targeted regions and sectors cover a wide range. It is interesting to find that the time scopes set by these studies are around 2030, partly because of the emissions peaking goal announced by the government. A few studies take the industry sector as a whole to analyze future emissions trajectories (Wang et al., 2019). Some studies attempt to investigate the potential role of different factors in achieving particular national emissions targets (Zhu et al., 2015), or the crucial factors in determining China's industrial emissions peaking time (Zhang et al., 2017).

There is another strand of research addressing uncertain scenario analysis of emissions pathways through energy system models that feature a detailed representation of the energy supply side. Many studies in this domain assess the potential contributions of emissions mitigation from the perspectives of technological innovation or climate policy. These modeling works or integrated assessment model-based studies tend to treat structural change in the economy implicitly (Lefèvre et al., 2022). For instance, projections are based on aggregated relationships between energy use and income per capita without reference to explicit structural change assumptions (Bauer et al., 2017; Lefèvre et al., 2022). A few studies use energy system models to conduct scenario analysis for China's industry sectors as a whole, lacking a detailed representation of individual sub-sectors (Zhou et al., 2018). However, the uncertain effect of industrial structure change is absent from these studies.

Despite the important insights gained from the previous research, there is a need for a deep investigation into structural change in the industry sectors and how it would impact the emissions profiles in an uncertain future. To fill this knowledge gap, we attempt to couple an additive nonparametric model with IDA and use an updated the dataset of the industry sectors categorized into four groups based on their emissions characteristics. We further use this hybrid modelling framework to perform scenario analysis consistent with the narratives of shared socioeconomic pathways (SSPs) to examine the impacts on emissions pathways through 2040 under uncertainty. A detailed description of the SSP narratives and a summary of the latest applications can be found in (O'Neill et al., 2020, 2017; Riahi et al., 2017).

3. Method and data

3.1 Overall framework

The overall research framework of the modeling approach is illustrated in Fig.1. This approach starts with linking an additive nonparametric model with the widely used IDA method, namely LMDI, to examine the contributions of the critical driving forces as well as their impacts on emission scenarios. Decomposition analysis has proved an effective tool for investigating the effects of typical driving factors such as gross domestic product (GDP), population and fuel mix, etc. Decomposition results based on historical data provide valuable information, which, however, should be complemented by reasonable assumptions about the future. The extrapolative analysis offers such an approach (Ang and Goh, 2019; Mahony, 2014), whereas the specific method to implement the concept varies.

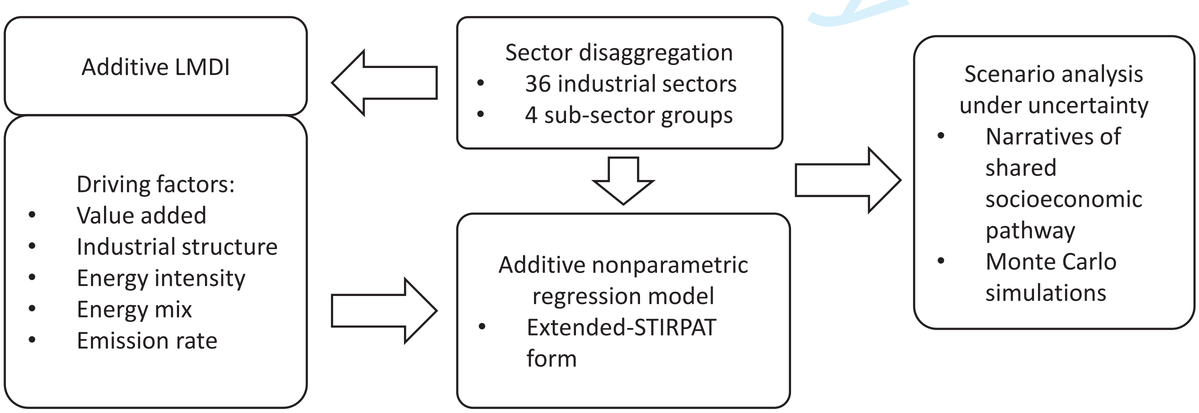

Fig. 1 Schematic diagram of the modeling approach in this study.

To investigate the structural change of these sectors, 36 industry sectors are categorized into four groups, namely, heavy industries with high energy intensity (HHE), new emerging industries (NEM), traditional light industries (TLI), and others (OTH). The detailed composition of each group is provided in the SM. The four groups represent the specific industry sectors with distinct characteristics. HHE refers to those process industries that are highly carbon-intensive and have more substantial environmental impacts, such as iron and steel making and cement production. On the contrary, NEM includes those high-tech manufacturing industries with considerable development potential, such as information and communication technology (ICT), medicine production, etc. TLI represents the traditional industries with relatively minor resource requirements and environmental impacts than HHE, including food processing, tobacco, textile, etc. OTH mainly consists of utility sectors.

We start by examining five key factors, namely, value added, industrial structure, energy intensity, energy mix, and emission rate. Following a conventional LDMI method, decomposition analysis is performed at both the sub-sectoral and the aggregated levels, through which the most influential factors are identified, selected and adopted in a nonparametric additive regression model. This regression model is constructed from extending a conventional STIRPAT model by retaining the linear part and incorporating the nonlinear effects from the critical driving factors selected from the decomposition analysis. The obtained regression form of the model is employed to project the emissions from the four groups of sub-sectors. The scenario settings for emissions projections, represented by a set of change rates of the crucial variables, are designed in line with the five narratives of SSPs (SSP1-SSP5). The time range for scenario analysis is set from 2020 to 2040, considering that this range covers and extends the horizon for reaching the emissions peak envisioned by the climate target. This setting allows to better illustrate how the uncertain structural change affects the emissions peaking target. Moreover, Monte Carlo simulations are performed to reflect the uncertain range of parameters in each SSP scenario. The following sub-sections describe the details of each component in this framework.

3.2 Decomposition analysis

We follow a standard additive LMDI approach and conduct a year-by-year decomposition and attribution analysis in order to closely trace the changes of key factors in specific sub-sectors. The total industrial emissions can be formulated as Eq. (1):

$$C = \sum_{ij} C_{ij} = \sum_{ij} Q \frac{Q_i}{Q} \frac{E_i}{Q_i} \frac{E_{ij}}{E_i} \frac{C_{ij}}{E_{ij}} = \sum_{ij} Q S_i I_i M_{ij} R_{ij} \tag{2}$$

where C is the total amount of industrial CO_2 emissions, C_{ij} is carbon emissions from the use of fuel j in industrial sector i, Q is total industrial output measured by value added, Q_i is the output of industrial sector i, E_i is the total amount of energy consumed in sector i, E_{ij} is the amount of fuel j consumed in sector i, S in industrial structure, measured by the output share of sector i in industrial output Q, I is energy intensity, measured by energy consumption for per unit output, M is energy mix, measured by the share of fuel j in total energy consumption of sector i.

The total changes of emissions in year T relative to those in the base year can be written in an additive form, as Eq. (2):

$$\Delta C_{tot} = C^T - C^0 = \Delta C_{act} + \Delta C_{is} + \Delta C_{ei} + \Delta C_{em} + \Delta C_{er} \tag{3}$$

where subscripts *tot, act, is, ei, em, er* denote the effects associated with overall activity level, industrial structure, energy intensity, energy mix, and emission rate, respectively. The detailed description of the calculation for all the components can be found in the SM.

3.3 The additive nonparametric model

3.3.1 The extended-STIRPAT model

The standard IPAT model decomposes aggregate environmental pressure such as carbon emissions into contributions from population growth (P), affluence (growth in per capita income or consumption, A), and technology advances (T) (Ehrlich and Holdren, 1971). Deriving from this approach, a STIRPAT model, known as Stochastic Impacts by Regression on Population, Affluence, and Technology, was proposed by Dietz and Rosa (Dietz and Rosa, 1997) to overcome some limitations of regression in the original IPAT model. The STIRPAT model has been widely used and adapted to analyze the correlation between environmental impacts and the abovementioned driving factors. The standard STIRPAT model taking logarithms is formulated as Eq. (3):

$$\ln C_{it} = a + b \ln P_{it} + c \ln A_{it} + d \ln T_{it} + e_{it} \tag{4}$$

where the subscript i denotes cross-sectional units, t denotes time period, the constant a and exponents b, c, and d are the elasticities of environmental impacts on population (P), affluence (A), and technology (T), and e is the error term. STIRPAT has been a popular tool for analyzing the influence factors of regional CO_2 emissions (Miao, 2017; Shahbaz et al., 2016; Wang et al., 2013).

Starting from the standard STIRPAT model, this study first substitutes the key driving factors under scope with the ones in line with industrial development, then establishes an additive nonparametric regression model to accommodate the nonlinear relationship between the variables.

The adjustments to the driving factors are presented below. As this model focuses on each industrial sub-sector, the effects of population and affluence are reflected in the valued added factor, therefore, the former two factors are replaced by industrial valued added. Second, the effect of technological advances is divided into two components, namely, energy intensity and energy mix. The two components differentiate technology improvements within the industrial manufacturing sub-sectors (e.g., through energy efficiency measures) from those in energy supply sectors (e.g., through promoting clean energy share in the supply mix). More details can be found in Section 4 and SM. The model is therefore formulated as Eq. (4):

$$\ln C_{it} = \beta_0 + \beta_1 \ln Q_{it} + \beta_2 \ln I_{it} + \beta_3 \ln M_{it} + e_{it} \tag{5}$$

The variables in the left and right sides of Eq. (4) are explained in Table 1, where C_{it}, Q_{it} , I_{it}, and M_{it} denote carbon emissions, value added, energy intensity, and energy mix for sector *i* at year *t*, respectively. Particularly, we use the share of coal-class fuels (such as raw coal, raw coal, cleaned coal, other washed coal, etc.) in total energy use to represent the energy mix.

Table 1 Definitions of the variables in the regression model

Variable	Definition	Unit
C	CO_2 emissions	Million tons (Mton)
Q	Value added	Billion yuan
I	Energy intensity, energy consumed per unit value added	Petajoule/Billion yuan
M	Energy mix, the share of coal in total energy consumption	Percentage

The linear regression form of Eq. (4) can be interpreted as an extension of the LMDI decomposition. The decomposition clearly illustrates the absolute contributions from each variable, whereas the regression is employed to demonstrate the direction as well as the independent relative change in the response variable over the explanatory variable while holding other variables constant. Nevertheless, the parametric model of Eq. (4) is inclined to oversimplify the unexpected characteristics and unknown relationships since it presumes the linear relationships between explanatory and response variables (Wang and Wang, 2011).

3.3.2 The nonparametric model

Nonparametric regression models exclude presumptions on the relationship between variables, which is considered an advantage over conventional parametric models. Yet they also have limitations such as the problem of high dimensionality. Nonparametric models in an additive form has been proposed to provide a compromise between the constrained linear model and the flexible nonparametric regression model (Buja et al., 1989; Xu and Lin, 2015). It uses a one-dimensional smoother in lieu of p-dimensional smoother for nonparametric regression models in order to avoid the curse of dimensionality (Buja et al., 1989). As such, they were also adopted to examine the relationship between CO_2 emissions and urbanization and industrialization (Xu and Lin, 2015). Following this approach, we further reformulate the model by adding the nonparametric components to Eq. (4). The new form is taken as Eq. (5):

$$\ln C_{it} = \alpha_0 + f_1(\ln Q_{it}) + f_2(\ln I_{it}) + f_3(\ln M_{it}) \tag{6}$$

where $f(\cdot)$ denotes a nonparametric function, with a shape not restricted to a specific parametric family such as polynomials, this representation is a key difference between parametric and nonparametric regression. Many methods such as kernel functions or spline-smoothing can be used for estimating the nonparametric models. Combining the linear part and the nonparametric part in an additive manner, we obtain the model formulated as Eq. (6):

$$\begin{aligned}\ln C_{it} = \alpha_0 + \beta_0 + \beta_1 \ln Q_{it} + \beta_2 \ln I_{it} + \beta_3 \ln M_{it} + f_1(\ln Q_{it}) \\ + f_2(\ln I_{it}) + f_3(\ln M_{it}) + e_{it}\end{aligned} \tag{7}$$

We use a spline approximation to the nonparametric components. With this approximation, each nonparametric component is represented by a linear combination of spline basis functions. In this way, $f(\cdot)$ is treated as a spline function, which consists of a linear combination of several basis functions. Denote $b(\cdot)$ as the basis function, λ_k as the unknown parameters, shown in Eq. (7):

$$f(x) = \sum_{k=1}^{K} \lambda_k \cdot b_k(x) \tag{8}$$

The regression spline estimator for $f(x)$ can be obtained by solving:

$$\hat{\lambda} = \arg\min_{\lambda} \sum_{n=1}^{N} (y_n - \sum_{k=1}^{K} \lambda_k b_k(x_n))^2 \tag{9}$$

The statistical problem is to determine which additive components are nonzero. There are different ways for variable selection in nonparametric additive models (Huang et al., 2010). Under suitable smoothness assumptions, the $f(\cdot)$ can be well approximated by functions in Eq. (8). In search for the estimators, an iterative procedure called the back-fitting algorithm is used to fit an additive model, which is also employed in this study. A more detailed description of the algorithm can be found in (Breiman and Friedman, 1985).

3.4 Data and assumptions

We collected the raw data with regards to value added and fuel consumption and other variables in the past two decades between 2000 and 2019, mainly from China's National Bureau of Statistics (China National Bureau of Statistics, 2021) and (China National Bureau of Statistics, 2021). Some boundary issues need to be addressed, where further processing is required. For example, the classification of industries has been adjusted several times. In the National Standard of Industrial Classification (GB/T4754-2011), Chinese industrial sectors are classified into three big categories: mining, manufacturing, and energy (electricity, gas, and water) production and supply. There are 7, 31, and 3 sub-sectors within each category, respectively. This classification was updated from the 2002 version, which contained 38 sub-sectors in total. To guarantee data consistency, we adjusted the classification into 36 sub-sectors throughout the entire period under this study. A detailed description of this new classification and the associated data processing are presented in the SM.

The output data used in this study is sub-industrial value-added at the constant price level. This study adopted the approach as proposed by (Chen, 2011) to cope with the reconstruction of statistical data of sub-industry sectors in China. The final energy carriers considered in this study are raw coal, cleaned coal, other washed coal, coke, coke oven gas, other gas, other coking products, crude oil, gasoline, kerosene, diesel, fuel oil, liquid petroleum gas (LPG), other petroleum products, natural gas, heat, electricity, and other energy carriers. Energy consumption data for the 36 sub-sectors are collected from (the China National Bureau of Statistics, 2021). Nevertheless, accounting emissions could also suffer from significant uncertainties with respect to heating value, carbon content, and oxidation rate. CO_2 emissions are calculated based on energy consumption and emission factors recommended by (IPCC, 2006; Shan et al., 2020). Moreover, the process-related CO_2 emissions, in particular from the cement industry, is calculated by the cement output and emission factor on an annual basis.

Fig. 2 shows the CO_2 emissions and the aggregated value added for the four grouped industry sectors between 2000 and 2019. The emissions of the four grouped industry sectors peaked at 7155 Mton in 2014 in the past two decades and then dropped by 2.3% in 2015, forming a plateu stage towards 2019. This drop mainly came from the six heavy sub-industry sectors identified as the key areas to implement the policies of "energy-saving and emissions reduction" by the government. Fig. S1 in the SM shows the largest shares of energy consumption came from the six energy intensive sectors, which collectively consumed 75% of energy in industry sectors or 51% of the national total.

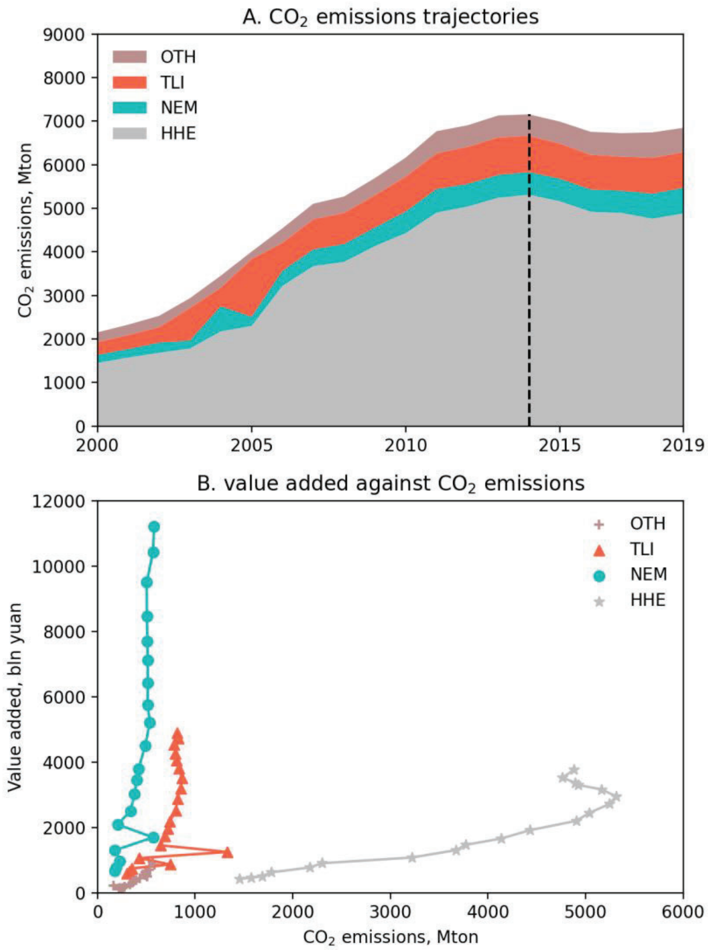

Fig. 2 CO_2 emissions and value added of the four sub-sector groups from 2000 to 2019. Note: HHE-heavy industry with high energy intensity, NEM-new emerging industry, TLI-traditional light industry, OTH-others.

4. Results and scenario analysis

4.1 Decomposition results

Decomposition analysis in this study is carried out over the entire time scope. Fig. 3 shows the results of decomposing the relative changes in China's industrial CO_2 emissions, measured as the change rate of CO_2 emissions for each year relative to the year 2000; this change is decomposed into the contributions of five factors, i.e., value added, energy intensity, industrial structure, energy mix, and emission rate.

293 The decomposition results show that the quick expansion of industrial production, represented by increasing value added, was the main driving force in the emissions, as its contributions increased by 4.5 times between 2000 - 2019. The energy mix also contributed positively to a small share of the emissions growth. On the contrary, energy intensity served as the primary factor for curbing emissions, which indicates a remarkable achievement of energy efficiency gains and technological advancement. The emissions reduction attributable to this energy efficiency and technological effect increased over time and are dominant in this period. In addition, industrial structural change also contributes to reduced emissions: it contributed 686 Mton emissions reductions between 2000 and 2013, and then increased reductions to 798 Mton between 2014 and 2019.

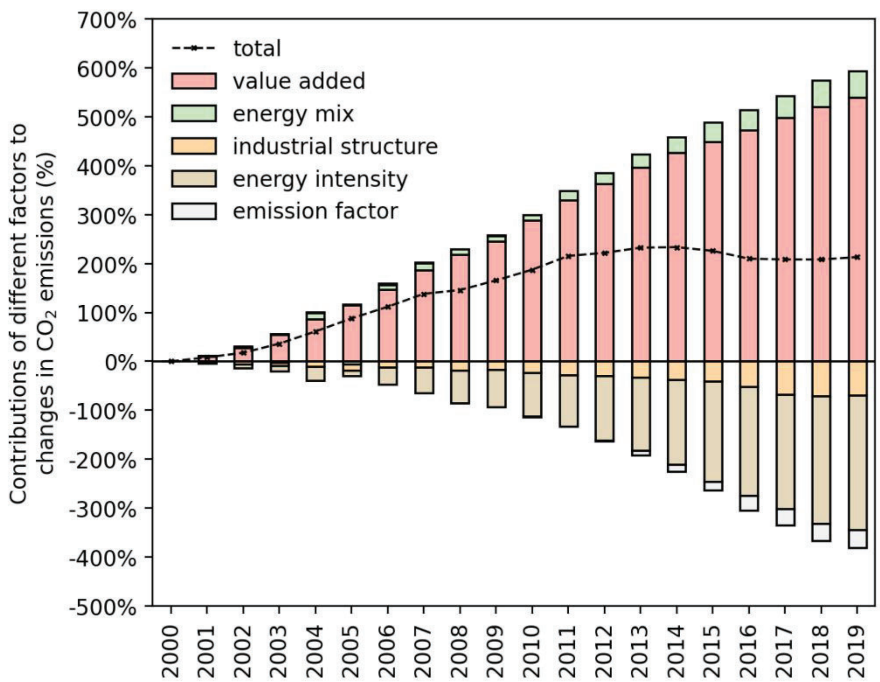

Fig. 3 Contributions of the five factors to the emissions change over time

These findings are in line with the conclusions from other studies. In addition, this study also performs an in-depth attribution analysis to examine the contributions from each of the 36 subsectors to the total emissions change. Fig. S2 in the SM shows the results of attribution analysis for the 36 sectors regarding their respective contributions to the emissions change resulting from value added and energy intensity. In particular, the six highest energy-intensive sectors collectively contributed 68% to the increased emissions resulted from value added, among which ferrous press accounted for 30%.

From 2014 to 2019, The trend of the aggregate industry emissions showed the first-ever consecutive decline over the last two decades. During this period, the growth of total national emissions also came to a halt, which has been discussed by some studies (Zheng et al., 2019). Fig. 4 zooms in the contributions of the four groups of sub-sectors and illustrates that the heavy industries, particularly ferrous press and nonmetal production, were the main contributors to this emissions change. It is interesting to find that although the expansion of heavy industry volume continued, industry structure upgrade and energy intensity improvement contributed 798 Mton and 2705 Mton emissions reduction, thereby offsetting the incremental emissions from scale expansion over this period.

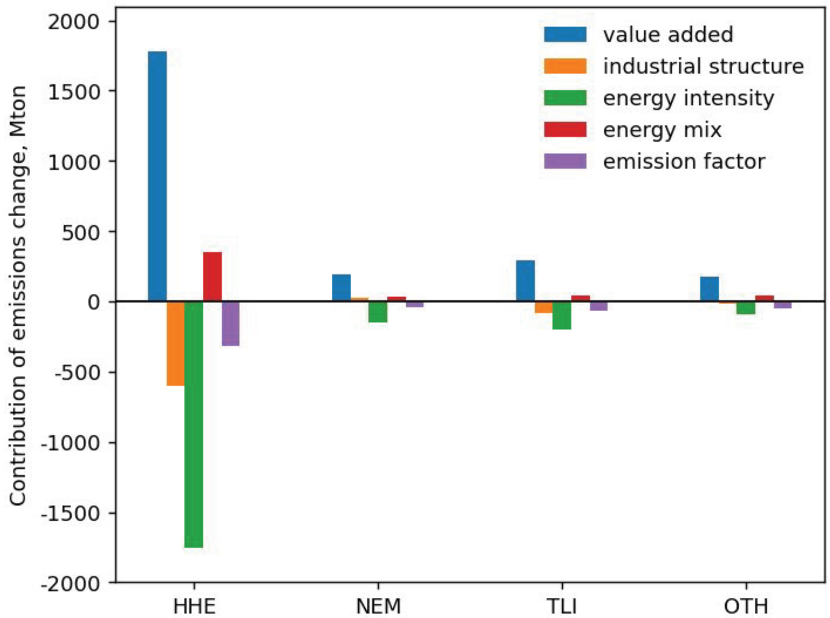

Fig. 4 Decomposed contributions to the total emissions reduction between 2014 and 2019.

Note: abbreviations in the x-axis, HHE-heavy industry with high energy intensity, NEM-new emerging industry, TLI-traditional light industry, OTH-others.

4.2 Model regression and empirical results

The estimation results of different linear models compared with the linear part of the nonparametric model are summarized in Table 2. More details, such as the results of the panel unit root test, are provided in the SM. The results suggest that the linear part coefficients are consistent with those of the linear models, despite some minor differences in significance levels. The results also show that the nonparametric model has a relatively small residual sum of squares (RSS).

Table 2 Estimation results: model comparison

Model	Variables	HHE	NEM	TLI	OTH
Nonparametric	Intercept	0.197***	-0.024	0.047***	0.140

model: linear part	ln*Q*	0.724***	0.659***	0.577***	0.483*
	ln*I*	0.453***	0.838***	0.855***	0.684***
	ln*M*	-0.301***	0.010	-0.007***	-0.245
	RSS	1.552	0.837	2.796	2.163
	R^2	0.995	0.99	0.992	0.974
	AIC	-294	-284	-385	-6.11
Linear fixed effects model	Intercept	-1.586***	-1.915***	-2.609***	-2.646***
	ln*Q*	1.039***	0.979***	1.078***	1.118***
	ln*I*	0.702***	0.863***	0.922***	1.017***
	ln*M*	-0.029	-0.071***	-0.275***	-0.225**
	RSS	7.764	1.334	5.144	4.238
	R^2	0.977	0.982	0.985	0.960
	F-statistic	2286***	2274***	4911***	412***
	Observations	180	144	252	72
Linear random effects model	Intercept	-2.073***	-2.030***	-2.097***	0***
	ln*Q*	0.989***	1.020***	1.001***	0.789***
	ln*I*	0.946***	0.826***	0.904***	0.629***
	ln*M*	-0.069**	0.021	-0.129***	-0.076
	RSS	0.955	1.166	3.334	3.336
	R^2	0.975	0.969	0.963	0.849
	F-statistic	2270***	1437***	2127***	129***
Pool model	Intercept	-1.372 ***	-2.040 ***	-2.328 ***	-2.333 ***
	ln*Q*	0.980 ***	1.004 ***	1.026 ***	1.082 ***
	ln*I*	0.744 ***	0.865 ***	0.939 ***	1.012 ***
	ln*M*	0.031	-0.061 **	-0.226 ***	-0.142 ***
	RSS	8.945	2.084	6.687	5.234
	R^2	0.976	0.979	0.982	0.954
	F-statistic	2386***	2122***	4389***	472***

Significance level: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

The results demonstrate that the established nonparametric model can not only grasp the linear relationship but also capture the nonlinear contributions from the key driving factors, including industrial volume, energy intensity, and energy consumption mix, to the sectoral carbon emissions. It thus functions as a proper tool for performing scenario analysis towards a mid-term future.

4.3 Scenario analysis

Emission scenarios in the mid-term future largely depend on the change of the three investigated variables, i.e., value added, energy intensity and energy mix. In this study, the constructed regression model is used for scenario analysis until 2040. The scenarios are set up following the narratives of the shared socioeconomic pathways (SSPs) (O'Neill et al., 2017; Riahi et al., 2017). Table 3 briefly describes the SSPs and summarizes how they are reflected in the scenario setup of this study, more specifically,

341 the change of the three driving factors representing relevant policies imposed in China's industry sectors
342 under each SSP. A detailed list of parameter settings is provided in Table S5 in the SM.

343 Table 3 Implementation of the SSP narratives in scenario analysis of this study.

	Brief description (O'Neill et al., 2017; Riahi et al., 2017)	Implementation in this study
SSP1	Sustainability – Taking the Green Road. Inclusive development that respects perceived environmental boundaries. Consumption is oriented toward low material growth and lower resource and energy intensity.	Innovation-oriented industrial development decoupled from environmental pollution. Fast growth of NEM, in contrast with a rapid decline of HHE, significant improvement in energy intensity.
SSP2	Middle of the Road. Technological trends do not shift markedly from historical patterns. Slow progress in achieving sustainable development goals.	Continuation of the current trend. Average-speed growth of NEM, along with a gradual decline of HHE. Slow progress made in energy intensity improvement.
SSP3	Regional Rivalry. Concerns about competitiveness and security, Consumption is material-intensive.	Slow growth of NEM, along with a continued growth rate of HHE as well as other industry sectors. Slow improvement of energy intensity.
SSP4	Inequality. Increasing disparities between an internationally-connected society that contributes to knowledge- and capital-intensive sectors of the global economy and a fragmented collection of lower-income, poorly educated societies.	Medium-speed growth of NEM and TLI, a continued slow expansion of HHE and OTH. Moderate improvement of energy intensity.
SSP5	Fossil-fueled Development-Taking the Highway. Economic and social development is coupled with the exploitation of abundant fossil fuel resources and the adoption of resource and energy-intensive lifestyles.	Relative high-speed growth of NEM, along with a medium-speed expansion of other sectors. Increasing trend of energy intensity.

344 Following these storylines, the evolving trends of the three key driving factors are calculated and
345 illustrated in Fig. S3 in the SM. A substantial difference can be observed between these scenarios. For
346 instance, the aggregated value added of all the 36 sub-sectors increases at the highest rate in SSP1 and
347 at the lowest rate in SSP3, mainly driven by different development patterns of the four industry groups.
348 The gap of value added between NEM and HHE expands significantly in SSP1. The volume of NEM was
349 approximately 2.8-fold the size of HHE in 2019. This ratio increases to 17.5 in 2040 in SSP1, whereas it
350 shrinks to 2.2 in SSP3, which assumes a positive growth rate of HHE as opposed to the negative rate in
351 SSP1. Change of energy intensity is relatively moderate. Nevertheless, the disparities across sectors and

scenarios are also striking. In 2040, SSP1 has half of the energy intensity for HHE compared to SSP5 where the development relies on fossil fuel consumption.

Emissions pathways in the five scenarios are presented in Fig. 5, where Panels A and B show the total emissions of the whole industry and the emissions of the four groups, respectively. The shaded areas represent the results of a 95% confidence interval. The total industrial emissions follow absolute declining trajectories in three scenarios, that is, SSP1, SSP2, and SSP4. SSP1 features the lowest level of emissions, dropping by 43% from 6723 Mton in 2019 to 3770 Mton in 2040. In contrast, SSP5 sees the highest emissions with an increase of two-thirds at the end of this period. The overall trend of the other scenario with an upwards trend, SSP3, is at a much more modest slope compared to SSP5. However, its uncertainty range shows a small possibility that the emissions might also decrease. Emissions peaking strongly relies on the evolvement of key driving factors such as energy intensity and energy mix.

Regarding structural change, another interesting finding is that even in the most optimistic scenario of SSP1, HHE still accounts for the largest share of the total industrial emissions. However, the contribution from HHE declines across all five scenarios. This share in 2040 ranges from 47% in SSP1 to 70% in SSP3, all of which is lower than the share in 2019. The most significant structural change in terms of value added occurs in SSP1, where NEM increases from 54% to 77% between 2019 and 2040, and HHE declines from 18% to 5% over the same period. SSP3 is characterized by a relatively stable structure, HHE and NEM make up 21% and 51% of the total value added in 2040, respectively. A comparison between these scenarios suggests that a significant structural change could slash emissions by 30-45% in 2040.

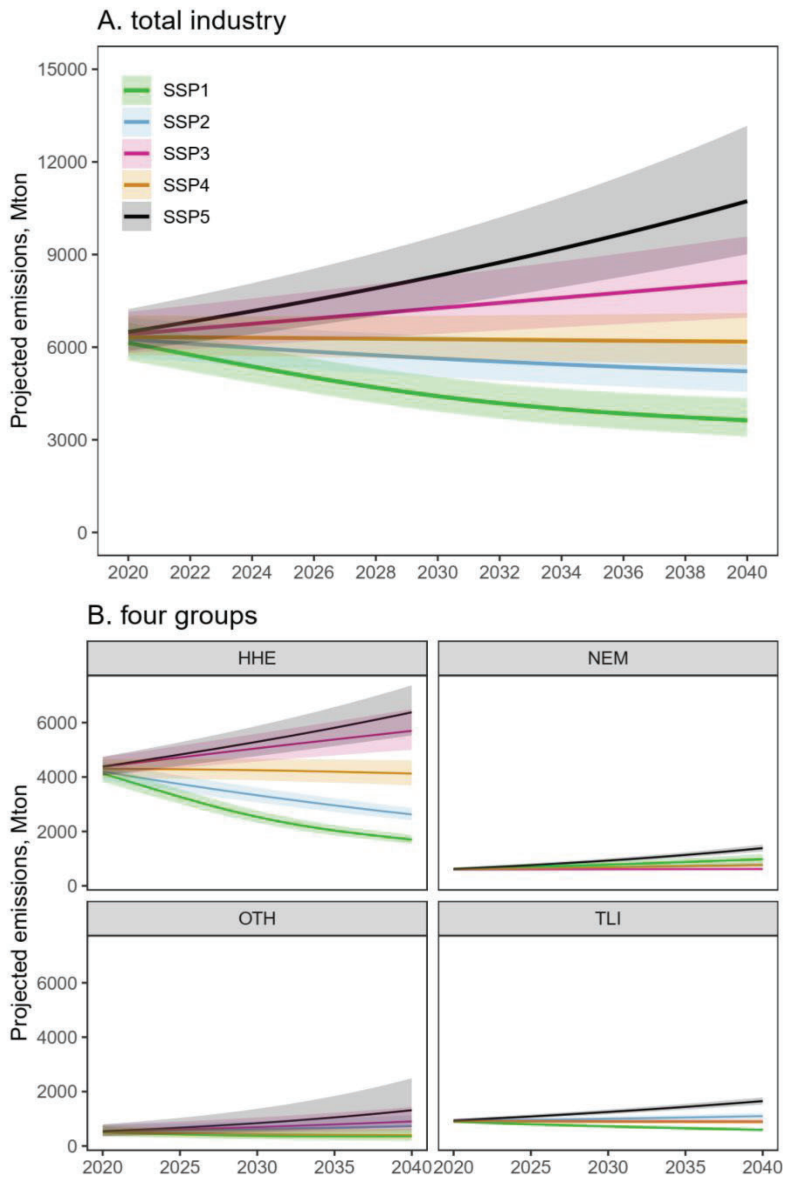

Fig. 5 Projected emission pathways of the industry sectors in the five scenarios. Note: HHE-heavy industry with high energy intensity, NEM-new emerging industry, TLI-traditional light industry, OTH-others.

5. Policy implications and conclusions

5.1 Enablers for the historical structural change

Our analysis shows that rapid increases in energy use and carbon emissions between 2000 and 2019 can be mainly explained by the expansion of heavy industries. Improvements in energy intensity (including industrial technology changes) and industrial structure became the dominant factors in curbing the increasing emission trend, in particular since 2014. More recent structural changes in China's industrial composition and development have significantly reduced the associated energy consumption and carbon emissions. These improvements can be partly attributed to the implementation of the "energy-saving and emissions reduction" policies over the last decade, in which the six highest energy-consuming subsectors were targeted by the government as the key areas for improvement. Energy consumption per unit GDP dropped by 19.1% and 18.2% over the periods of the 11th five-year-plan (FYP, 2005-2010) and the 12th FYP (2010-2015). Further, a target of a 15% decrease in this indicator between 2015 and 2020 was set by the 13th FYP (China State Council, 2016). In this context, a few studies analyzed the possible turning point in recent years for China's coal use and its impact on CO_2 emissions. Qi et al. argued that China's economic growth seems to have decoupled from an increase in coal consumption, thanks to a structural shift away from heavy industry, and more proactive policies on air pollution and clean energy have caused China's coal use to peak (Qi et al., 2016). Jackson et al. pointed out rapid growth in global CO_2 emissions from fossil fuels and industry ceased in 2014 and attributed this to decreased coal use in China (Jackson et al., 2016). The year 2014 also marks a watershed in the transition of China's industrialization process. Before 2014, the expansion rates of the six emission-intensive sectors outpaced their improvements in energy efficiency, resulting in increased industrial energy consumption and emissions. However, structural changes seemed to speed up after 2014, as many heavy industry sectors faced overcapacity. For example, the average capacity factor of crude steel and coal production in China both dropped even below 70% in 2015 (China Iron and Steel Association, 2019). At the same time, their energy use for per unit production kept decreasing, implying a continuing trend of energy efficiency and emissions reduction in both sectors.

5.2 Implications of reaching emissions peak and carbon neutrality

A deep understanding of the driving forces behind the historical changes will improve the future projection of energy consumption and carbon emissions. The scenario results in this study suggest that regardless of the uncertainty reflected in scenario settings, heavy industry will continue to be the largest share of total industrial emissions across all the five scenarios through 2040. This indicates that mitigating emissions from these industry sectors through multiple measures is pivotal to reaching the ambitious targets. Transitioning towards innovation-driven industrial development is thus one of the most important mitigation measures to be taken. Our study suggests a significant structural change in sub-industry sectors could lead to a 30-45% emissions reduction in 2040 compared to the cases with minor structural improvements.

As China enters an era of post-industrial development, the share of industry sectors in the economic outputs has been shrinking. In 2019, industrial value added comprised approximately 33% of the total GDP, decreasing from the share of 40% in 2001 (China National Bureau of Statistics, 2021). The central government also launched the so-called “supply-side structural reform” in 2015 by focusing on five key tasks: cutting overcapacity, destocking, deleveraging, lowering costs, and improving weak links (China National Bureau of Statistics, 2021). To achieve excessive capacity reduction, the government launched a supply-side structural reform and met the yearly target of reducing 45 Mton of steel and 250 Mton of coal production capacity ahead of schedule before the end of 2016 (China National Bureau of Statistics, 2020). Although the development of these emissions-intensive sectors remains uncertain in the future, it is more likely that innovation-driven manufacturing sectors will take the lead in powering the new economic engine.

In pursuit of sustainable development, China’s government seeks to continually upgrade its industrial structure by proposing measures such as emissions trading schemes and financing green development. These measures anticipate the need to shape to a large extent patterns of energy consumption and CO_2 emissions in the future. If this trend continues, the government’s target of peak emissions by 2030 would be achievable. Nevertheless, reaching carbon neutrality depends not only on industrial structural change but also on other factors such as low-carbon or zero-emission energy systems and the implementation of negative emissions technologies.

5.3 Limitations and implications for future research

This study attempts to address uncertainty in future structural change by employing a combination method of scenario analysis and Monte Carlo simulations to cover a wide range of possibilities. Despite these efforts, the results from this study are also reflect methodological limitations, limitations in the accuracy of energy statistics, and of carbon emissions accounting methods. In addition, a detailed bottom-up model for examining a disruptive energy system transformation could be developed to perform cost-benefit analysis of more decarbonization pathways for industry sectors. Moreover, how specific policy instruments would impact both supply-side and demand-side of each industry sub-sector could provide more granular information for a further deepened analysis.

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[1] This share excludes construction. In the national economy accounting categories, “the secondary industry” includes both industry and construction, whereas in this study, industry comprises those sub-sectors belonging to mining, manufacturing and electricity, water and gas supply, more detailed description of these sectors can be found in Supporting Information.

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