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China's pathways to peak carbon emissions: New insights from various industrial sectors

Kai Fang [a,b,c], Chenglin Li [a], Yiqi Tang [d,*], Jianjian He [a], Junnian Song [e]

[a] School of Public Affairs, Zhejiang University, Hangzhou 310058, China
[b] Center of Social Welfare and Governance, Zhejiang University, Hangzhou 310058, China
[c] Zhejiang Ecological Civilization Academy, Anji 313300, China
[d] School of Public Policy and Management, Tsinghua University, Beijing 100084, China
[e] College of New Energy and Environment, Jilin University, Changchun 130012, China

HIGHLIGHTS

- Tracking carbon emissions historical trend in China's eight industrial sectors.
- Regression analysis and Monte Carlo simulation to predict emissions trajectories.
- *Agriculture*, *Building*, *Others* and *Transportation* are likely to peak before 2025.
- *Electricity* and *Mining* may peak after 2030, while *Business* remains unclear.
- Focusing on the emissions of various sectors facilitates meeting the Paris Agreement by 2030.

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ABSTRACT

To maintain global warming below 2 °C, as per the Paris Agreement, China should stop its energy-related carbon emissions from increasing by 2030. Given the dominating role of industrial-specific emissions in the national emissions inventory, exploring the potential peaking pathways of emissions in China's diverse industrial sectors is necessary. By accounting for the emissions from China's eight sectors over the past 23 years, this study examines the Environmental Kuznets Curve hypothesis for the eight sectors using both regression analysis and Monte Carlo simulation. We found that seven out of the eight sectors are expected to reach their peak emissions before 2040, despite continued economic growth. Specifically, emissions from the *Agriculture*, *Building*, *Manufacturing*, *Others*, and *Transportation* sectors are highly likely to peak before 2030, while those from the *Electricity* and *Mining* sectors may peak after 2030. Our findings, which provide a deeper understanding of China's potential peaking pathways at the sectoral level, can serve as a reference for other countries that are facing similar difficulties in identifying the appropriate ways of peaking sectoral emissions; this is currently a neglected field of analysis in many Nationally Determined Contributions.

1. Introduction

The climate change associated with carbon emissions poses unprecedented threats to the international community, such as extreme weather, sea-level rise, infectious diseases, biodiversity loss, and food shortage [1]. To mitigate climate warming, a consensus was reached worldwide that end-of-century warming must be maintained below 2 °C, or even 1.5 °C above the pre-industrial levels [2–4]. To this end, a growing number of nations have recently committed to realizing net-zero emission systems that do not increase the atmospheric carbon concentration by 2050 [5–6]. However, global emissions continue, reaching a record-high level of 33.3 Gt in 2019 [7]. While this trend has been reversed during the COVID-19 pandemic, with a 17% reduction in global daily emissions, compared with the average level in 2019, this reduction may be temporary, because no evidence supports any structural changes to the world's industrial systems [8]. Retaliatory emissions are likely to occur after the industrial production activities recover. As such, slowing down global warming by reducing industrial emissions

* Corresponding author.
E-mail address: tangyq20@mails.tsinghua.edu.cn (Y. Tang).

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remains a top priority among long-term strategies for global environmental governance [9–10].

China is the largest emerging economy worldwide, which accounted for approximately 30% of the global carbon emissions in 2019 [11]. Unlike most of the G20 nations that aim to reduce their national emissions to a certain level in their individual Nationally Determined Contributions (NDCs), China has announced its aim to reach peak emissions in its NDCs by 2030 [12], and further become carbon neutral by 2060 [13]. Officially, China's total emission allowance before 2030 is not yet determined; it has been allocated to different provinces and cities where emission reduction actions are primarily implemented [14]. As China has planned to sustain its economic growth through the massive development of infrastructure and investment in the manufacturing sector [15],the likelihood that China's emissions will peak in the coming decade becomes increasingly uncertain. However, China must reach its peak emissions to fulfilling the global 1.5 °C or 2 °C goals, which has attracted enormous attention from academia over the past few years. The estimates, however, often appear to be divergent, even contradictory [16–17]. Many argue that China's carbon emissions may peak at the national level by 2030, more likely between 2025 and 2030 [18–20] , while others object to this argument [21–22].

Given the dominating role of industrial-specific emissions in the national emissions inventory, several studies have focused on the peaking paths of several industrial sectors, such as transportation [23], textile [24], and building sectors [25]. Further. China has entered an advanced stage of industrialization [26]; emissions in industrial sectors are expected to peak first, without which a nationwide peaking of emissions would be impossible. This highlights the complexity and diversity of various industrial sectors. For instance, energy-related emissions in energy-intensive industries are more likely to peak faster, compared with those in light industries [27]. Specifically, emissions in the cement and steel sectors are predicted to peak by 2020 [28–30]. Those in the electricity sector, between 2020 and 2030 [31–32]; those in the petrochemical sector, around 2030 [33]; and those in the transportation and building sectors, between 2030 and 2035 [34–35]. The industrial sectors' diversified emission trajectories increase the complexity and uncertainty of China's goal to have peak emissions before 2030 [36]. Therefore, narrowing the focus to a single or few sectors is therefore insufficient to represent industrial emissions that substantially vary across sectors [37]. For this reason, we argue that a multi-sectoral perspective can provide novel insights into the potential peak emission pathways in China. However, to the best of our knowledge, future emissions between various industrial sectors in China have not been analyzed comparatively in the existing literature, and no studies translate China's peaking goal into the sectoral levels.

To predict future emissions and peaking paths, the Environmental Kuznets Curve (EKC) hypothesis can be examined in many ways using econometric models [38]. Furthermore, by incorporating scenario analysis into the econometric study, the possible emission trends can be understood [16]. Scenario analysis can be broadly divided into two categories: static and dynamic [39]. Current scenario analyses often include arbitrary scenario settings that assume a fixed rate of changes in variables [27]. Despite the broad spectrum of applicability, this approach is flawed in that quantitative uncertainty analysis is either lacking or replaced by sensitivity analysis, which can create an overly simplistic estimation of uncertainty [40]. The omission of uncertainties cannot be ignored; specifically, if some extreme scenarios rarely occur, they should not be treated like other scenarios.

To overcome the shortcomings of static scenario analysis, dynamic scenario analysis was employed. As a mainstream dynamic scenario analysis, Monte Carlo simulation has been envisaged to quantify uncertainty by distributing probabilities to key variables, based on historical data or expert judgments [41]. Unlike deterministic approaches, Monte Carlo simulation can be perceived broadly as a stochastic method that is appropriate for addressing problems that involve diverse, and even conflicting, uncertainties [42]. Monte Carlo simulation has become increasingly popular over the past few years because of uncertainty testimonies [43], with applications at scales ranging from a single sector [44], cities [45], and nations [46], among others. [45]. By providing a scientifically robust methodology for predicting different variables with uncertainty range, Monte Carlo simulation facilitates the identification of likely emission trajectories, instead of the fixed assumptions of some variables [47–48].

In this study, we investigate the emission trajectories of various industrial sectors in China using both regression analysis and Monte Carlo simulation to identify desirable pathways for different sectors to reach peak emissions. This sector-level investigation would also be informative for other nations, such as India—the country that is expected to replace China as the world's largest carbon emitter in the coming years. In summary, the novel contributions of this study to the literature are threefold: (1) they present a full picture of China's future emission trajectories for eight industrial sectors for the first time. (2) This study combines regression analysis and Monte Carlo simulation to examine the EKC hypothesis with transparent and comprehensible uncertainty estimates, and (3) the focus on peaking emissions is shifted from the national level to the sectoral level, which is key in achieving the NDCs' goals that have been neglected for a long time.

2. Methods and data

2.1. Sectoral carbon emissions accounting

This study accounts for China's carbon emissions that are relevant to energy consumption at both sectoral and national levels using the following formula:

$$C_s = \frac{44}{12}\sum_{i=1}^{4}(F_{s,i}E_{s,i}) \quad (1)$$

where C_s is the carbon emissions of sector s, F_i^s is the carbon emission factors for energy I, and $E_{s,i}$ is the amount of consumption of sector s in energy i. Energy consumption could be classified into four types: coal, oil, natural gas, and non-fossil, all of which are then converted into standard coal, as per their respective heat values [49]. The emission factors are obtained from China's Energy Research Institute [50].

2.2. The EKC hypothesis and regression analysis

We employ a quadratic regression model to test the existential EKC hypothesis for the carbon emissions and GDP per capita in each sector using the following formula:

$$\ln C_s = a + b\ln \mathrm{GDP}_{st} + c(\mathrm{GDP}_{st})^2 + \varepsilon_s \quad (2)$$

where GDP_{st} is the GDP per capita at time t of sector s; a, b, and c are the coefficients that need to be determined; and ε is an error term representing all the other variables that may affect emissions.

While ordinary least square regression is applied to the parameter estimation typically, its ability to deal with the multicollinearity of different independent variables is limited [51]. Furthermore, if time-series data lack co-integration, the regression results of co-integration methods such as the benchmark regression may be biased [52]. The autoregressive distributed lag (ARDL) method has been broadly adopted in many research fields [30,53–54]. The advantages of the ARDL method, over other regression methods, include (1) a lower requirement of time-series data for sample size and no requirement for robustness testing; and (2) it can provide unbiased and valid evaluation, even if the independent variables are endogenous [55–56]. As such, the ARDL method is employed in this study for regression analysis using the following formula:

$$\Delta lnC_{st} = a_0 + \sum_{k=1}^{n1} a_{k1}\Delta lnC_{s,t-k} + \sum_{k=1}^{n2} a_{k2}\Delta ln\mathrm{GDP}_{s,t-k} + \sum_{k=1}^{n3} a_{k3}\Delta\left(ln\mathrm{GDP}_{s,t-k}\right)^2 + \delta_1 lnC_{s,t-1} + \delta_2 ln\mathrm{GDP}_{s,t-1} + \delta_3\left(ln\mathrm{GDP}_{s,t-1}\right)^2 + \varepsilon_{st} \quad (3)$$

where $C_{s,t}$, $C_{s,t-k}$, and $C_{s,t-1}$ are the carbon emissions of sector *s* at time *t*, *t-k,* and *t*-1, respectively. $C_{s,t-k}$ is the carbon emissions of sector *s* at time *t*-k; $\mathrm{GDP}_{s,t-k}$ and $\mathrm{GDP}_{s,t-1}$ are the GDP per capita of sector *s* at time *t-k* and *t*-1, respectively; δ_1, δ_2, and δ_3 are the coefficients of the lags of $lnC_{s,t-1}$, $ln\mathrm{GDP}_{s,t-1}$, and $\left(ln\mathrm{GDP}_{s,t-1}\right)^2$, respectively; a_0 and ε_{st} are the constant and error terms, respectively; and a_{k1}, a_{k2}, and a_{k3} are the parameters to be determined.

2.3. Monte Carlo simulation

Scenario analysis serves as a valuable tool for projecting carbon emissions pathways at multiple scales [42]. In this study, Monte Carlo simulation is performed as a scenario analysis that forecasts the carbon emissions from China's eight sectors. The Monte Carlo simulation process consists of three steps. First, we define prior probabilities for critical variables that drive carbon emissions, such as GDP per capita. As the probability distribution of these variables is not precisely known, randomly selecting the rates at which the drivers change is more suitable for applying the triangular distribution function [57]. Second, multiple simulations are conducted by distributing a random sample variable range based on the pre-defined probability. In our case, each industrial sector implements 100,000 simulations, as a more significant number of simulations produces more accurate results. Third, the results of GDP per capita simulation, accompanied with frequency distributions, provide possible output values. By doing so, Monte Carlo simulation facilitates a more accurate evaluation of the future GDP per capita and carbon emissions for each industrial sector in China.

2.4. Data

For consistency, we collected the data of China's 56 sectors for the period 1995–2017 and aggregated them into eight major industrial sectors: *Agriculture*; *Building*; *Business*; *Manufacturing*; *Mining*; *production and distributions of electricity, heat, gas, and water* (*PDEHGW)*; *Building*; *Others;* and *Transportation* as per the new Chinese industrial classification standard in 2002. The components of the eight industrial sectors are displayed in Table 1. Data sources are presented in Table 2. The industrial value-added data are derived from the China Industry Economy Statistical Yearbooks (1996–2018) and China Economic Census Yearbook (2004). The data on GDP has been converted to compare prices in 2010.

Table 2
Data sources for critical variables.

Variable	Description	Data sources
Carbon emissions	Total carbon emissions from energy consumption	China Energy Statistical Yearbooks (1996–2018)
GDP per capita	Total GDP of a sector divided by end-year employment of the sector	China Economic Census Yearbook (2004), China Industrial Statistical Yearbooks (1996–2018) China Industry Economy Statistical Yearbooks (1996–2018), China Statistical Yearbooks (1996–2018)
Population	Employment by sector at the end of a year	China Statistical Yearbooks (1996–2018)

Table 1
Classification of China's eight industrial sectors is composed of 56 sub-sectors.

No.	Industrial sectors	Sub-sectors
1	*Agriculture*	Agriculture, Farming of animals, Farming of animals and fishing, Fishing, Forestry, Service activities for agriculture
2	*Building*	Architectural decoration, Architectural installation, Construction of building & Civil engineering, Other construction
3	*Business*	Accommodation and restaurants, Wholesale and retail trade
4	*Manufacturing*	Agricultural non-staple food processing, Beverage production, Chemical fiber products, Cultural, educational and sports articles, Electrical machinery and equipment, Food production, Furniture manufacturing, Papermaking and paper products, Garments and other fiber products, General purpose machinery, Leather, furs, down and related products, Measuring instrument machinery, Medical and pharmaceutical products, Metal products, Nonmetal mineral products, Petroleum and nuclear fuel processing and coking, Printing and recording medium reproduction, Raw chemical materials, and chemical products, rubber and plastic products, Smelting and pressing of ferrous metals, smelting, and pressing of nonferrous metals, Special purpose machinery, Telecommunication, and other electrical equipment, Textile industry, Timber processing, bamboo, cane, palm fiber and straw products, Tobacco processing, Transportation equipment
5	*Mining*	Coal mining and dressing, Ferrous metals mining and dressing, Nonferrous metals mining and dressing, Nonmetal minerals mining and dressing, Petroleum and natural gas extraction
6	*PDEHGW*	Production and distribution of electricity and heat power, Production and distribution of gas, Production, and distribution of water
7	*Others*	Other sectors in the tertiary industry, such as Culture, sports and entertainment, Education, Finance, Information transmission, software, and information technology, Professional technique services, Public management, social security and social organization, Real estate Tenancy and business, Research, and experimental development, Sanitation, social security and social welfare, Scientific research and technical service, Scientific research, technical service and geologic perambulation, Service to households, repair, and other services
8	*Transportation*	Transportation, Storage, and Post

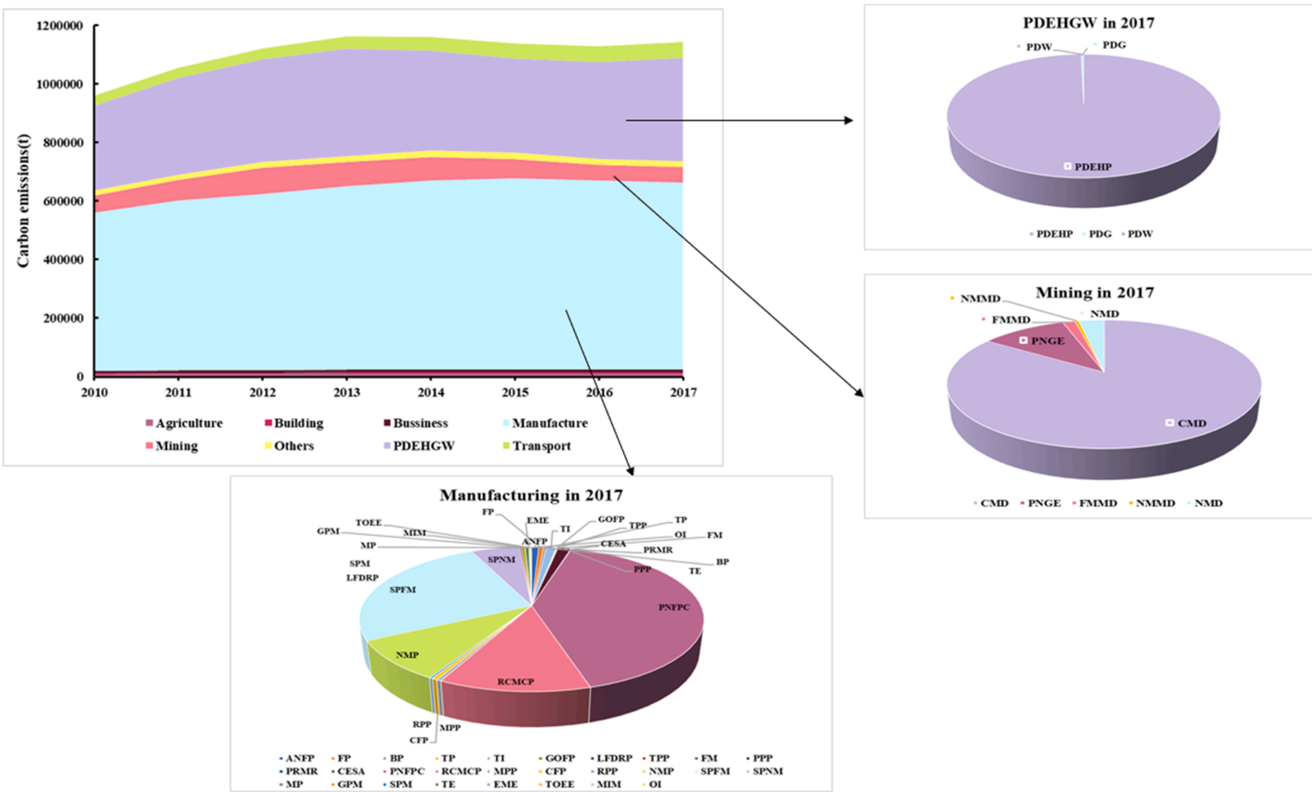

Fig. 1. Trends in the carbon emissions of eight industrial sectors. We also provide a detailed sub-sectoral composition of the top-three emitters. Abbreviations of these subsectors can be found in Table S1.

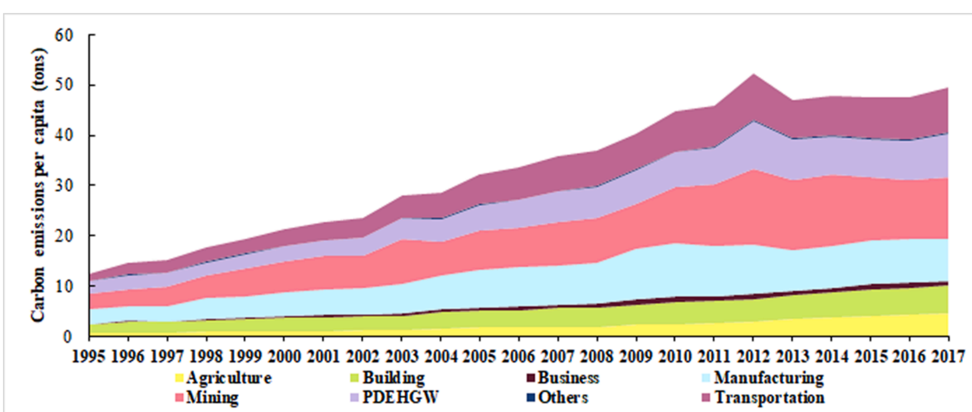

Fig. 2. Trends in the carbon emissions per capita of eight industrial sectors.

3. Results

3.1. Carbon emissions accounting

In the past decades, industrialization has driven the rapid increase in China's carbon emissions. Emissions from heavy industrial sectors, such as the *Manufacturing, Mining,* and *PDEHGW* sectors, have risen from 0.21 to 1.81 billion tons from 1995 to 2017 (Fig. 1), accounting for more than 70% of the total emissions from the eight sectors. Of these, over 56% of the emissions can be attributed to the *Manufacturing* sector, followed by the *PDEHGW*, *Transportation*, and *Mining* sectors, with shares of 30%, 5%, and 5% in 2017, respectively. In contrast to the decreasing trend in the emissions from the *Manufacturing* and *Mining* sectors, the increasing emissions from the *Agriculture, Building, Transportation,* and *Others* sectors are observed. As of 2017, the remaining industrial sectors, namely *Others* (1.8%), *Agriculture* (0.9%), *Business* (0.4%), and *Building* (0.8%), collectively made up approximately 4% of the total values.

For the emissions per capita (Fig. 2), the *Manufacturing, Mining, PDEHGW*, and *Transportation* sectors are the top four emitters, with an average annual growth rate of 7%, 5%, 14%, and 17%, respectively. The lowest and highest annual growth rates are found in *Agriculture* and *Building* sectors, with an estimated 2% and 18%, respectively. The *Business* and *Other* sectors, often classified as the tertiary industry, have lower emissions per capita, compared with the rest of the sectors. As of 2017, the *Manufacturing* sector was producing 145 times the emissions per capita of the *Business* sector.

Table 3
Unit root test (DF-GLS) for eight industrial sectors.

Sectors	Test var. (x)	Level (T-statistic)	1st diff. (T-statistic)
Agriculture	lnC	−0.048	−3.264***
	lnGDP	−0.163	−2.643**
	$(\ln GDP)^2$	−0.090	−2.724***
Building	lnC	−1.739*	−4.208***
	lnGDP	−2.385	−3.612***
	$(\ln GDP)^2$	−1.534	−3.208***
Business	lnC	−2.592	−4.808***
	lnGDP	−3.761***	−2.048**
	$(\ln GDP)^2$	−2.958***	−3.724***
Manufacturing	lnC	−2.307**	−2.753**
	lnGDP	−1.417	−2.241***
	$(\ln GDP)^2$	−2.768**	−2.038***
Mining	lnC	−2.095**	−4.828***
	lnGDP	−1.110	−2.092***
	$(\ln GDP)^2$	−0.182	−4.255***
PDEHGW	lnC	−0.827	−4.211***
	lnGDP	−0.750	−4.088***
	$(\ln GDP)^2$	−1.792**	−4.238***
Others	lnC	−0.744	−5.039***
	lnGDP	−0.735	−3.705***
	$(\ln GDP)^2$	−0.067	−3.608***
Transportation	lnC	−0.827	−4.211***
	lnGDP	−2.798**	−4.062***
	$(\ln GDP)^2$	−1.792*	−4.238***

Note:***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively. The same below.

Table 4
ARDL bound test cointegration for eight industrial sectors.

	Sectors	Optimal AIC lags	F-statistics	Cointegration exist or not
Estimated model FC (LLC/ LnGDP, $LnGDP^2$)	*Agriculture*	(2,1,1)	4.551**	Yes
	Building	(2,1,2)	22.891***	Yes
	Business	(2,1,0)	5.135**	Yes
	Manufacturing	(1,1,0)	17.792***	Yes
	Mining	(1,2,1)	12.436***	Yes
	PDEHGW	(1,1,0)	14.516***	Yes
	Others	(1,1,0)	35.197***	Yes
	Transportation	(1,1,2)	8.126***	Yes
	Critical values of Pesaran et al. [59], N = 30			
Significance level	Lower bound I (0)		Upper bound I (1)	
1%	4.614		5.966	
5%	3.272		4.306	
10%	2.676		3.586	

Notes: The critical values are collected from Pesaran et al. [59]. AIC determines the optimal lag length.

3.2. The EKC hypothesis testing

The first step in analyzing time series data is to determine whether they are stationary. To achieve this goal, we chose the Generalized least-squares detrended augmented Dickey-Fuller test (DF-GLS) unit root tests because it is more suitable for small samples, compared to other unit root tests. The results displayed in Table 3 show that the logarithmic sequence of three variables (i.e., carbon emissions per capita, GDP per capita, and the square of GDP per capita) for all eight sectors are stable at the 1% or 5% significance levels. In contrast, the logarithmic sequence of the variables for the *Building, Business, Manufacturing, Mining, PDEHGW*, and *Transportation* sectors are stable at the 5% or 10% significance levels. In sum, all the variables used in this study are consistent with I (0) or I (1) stationery. Therefore, they can be used for the estimation of the ARDL model.

The ARDL bound test is appropriate for small-sized samples with practical estimation and high tolerance of bound [58–59]. The ARDL bound test is used to examine the co-integrating relationships among the eight sectors. First, it is necessary to determine the optimal lag length based on the Akaike information criterion (AIC). Table 4 shows the results of lag order selection.

Table 5
ARDL regression analysis for eight industrial sectors.

Sectors	LnGDP	$(LnGDP)^2$	EKC holds	Turning point (RMB)	GDP per capita in 2017
Agriculture	3.573*** (0.891)	−0.170*** (0.048)	Yes	37,281	29,650
Building	6.555** (3.293)	−0.308** (0.172)	Yes	46,631	20,927
Business	3.803* (2.964)	0.862* (0.542)	No	None	13,249
Manufacturing	0.381* (0.094)	−0.017* (0.621)	Yes	71,396	51,883
Mining	21.829* (16.104)	−1.012* (0.778)	Yes	55,050	45,177
PDEHGW	2.408* (2.263)	−0.107* (0.058)	Yes	80,821	57,941
Others	1.424** (0.473)	−0.064** (0.146)	Yes	86,452	39,991
Transportation	2.371*** (0.738)	−0.088** (0.039)	Yes	53,236	44,048

Notes: Standard errors are provided in parentheses.

We test the EKC hypothesis, in which the carbon emissions per capita of China's eight industrial sectors are dependent variables. After introducing the panel data for the period 1995–2017 into the ARDL method, the corresponding sectoral GDP per capita and its square become independent variables. The regression results for all the sectors are displayed in Table 5. As shown, the EKC hypothesis holds for seven industrial sectors, in which GDP per capita exhibits an inverted U-shaped relationship with sectoral emissions per capita. We find that the GDP per capita has the most significant impact on the emissions from the *Agriculture* sector, followed by the *Building* and *Transportation* sectors. The emissions from the *Manufacturing, Mining, PDEHGW,* and *Others* sectors correlate significantly with economic growth. Regarding the *Business* sector, however, no evidence supports the EKC hypothesis. Instead, a linear correlation has been observed, implying that the *Business* sector is unlikely to reach peak emissions in the coming years. This suggests that there is much room for the development of the *Business* sector, partially because most of the sub-sectors, such as the Accommodation and restaurants and Wholesale and retail trade in the *Business* sector, appear to be environmentally friendly—they do not involve excessive material production and burning of fossil fuels [60].

In contrast to the *Business* sector, the emissions in all the other industrial sectors tend to peak when the corresponding GDP per capita reaches a turning point. The *Agriculture* sector was observed to have the lowest turning point, with a GDP per capita of 37,281 RMB. This is followed by the *Building*, *Transportation*, *Mining*, *Manufacturing*, and *PDEHGW* sectors. The *Others* sector had the highest turning point, with a GDP per capita of 86,452 RMB. Furthermore, we estimate the number of years that are required for each sector to reach the peak emissions at an average growth rate over the past 13 years. The gaps between current GDP per capita and estimated turning points vary substantially across industrial sectors, ranging from 7,631 RMB for the *Agriculture* sector to 46,461 RMB for the *Others* sector in absolute values. Such variations warrant an in-depth discussion on the differentiated pathways to peak China's emissions at the sectoral level, rather than narrowing the focus to the whole country or considering various industries as one sector.

3.3. Monte Carlo simulation

Considering all the economic growth scenarios under the existing policies, we explore the probability distributions of GDP per capita through Monte Carlo simulation over 100,000 times. By exploring the correlation of peak emissions per capita and the corresponding GDP per capita further, we noted prominent differences between different industrial sectors. As mentioned above, the highest turning point (86,452

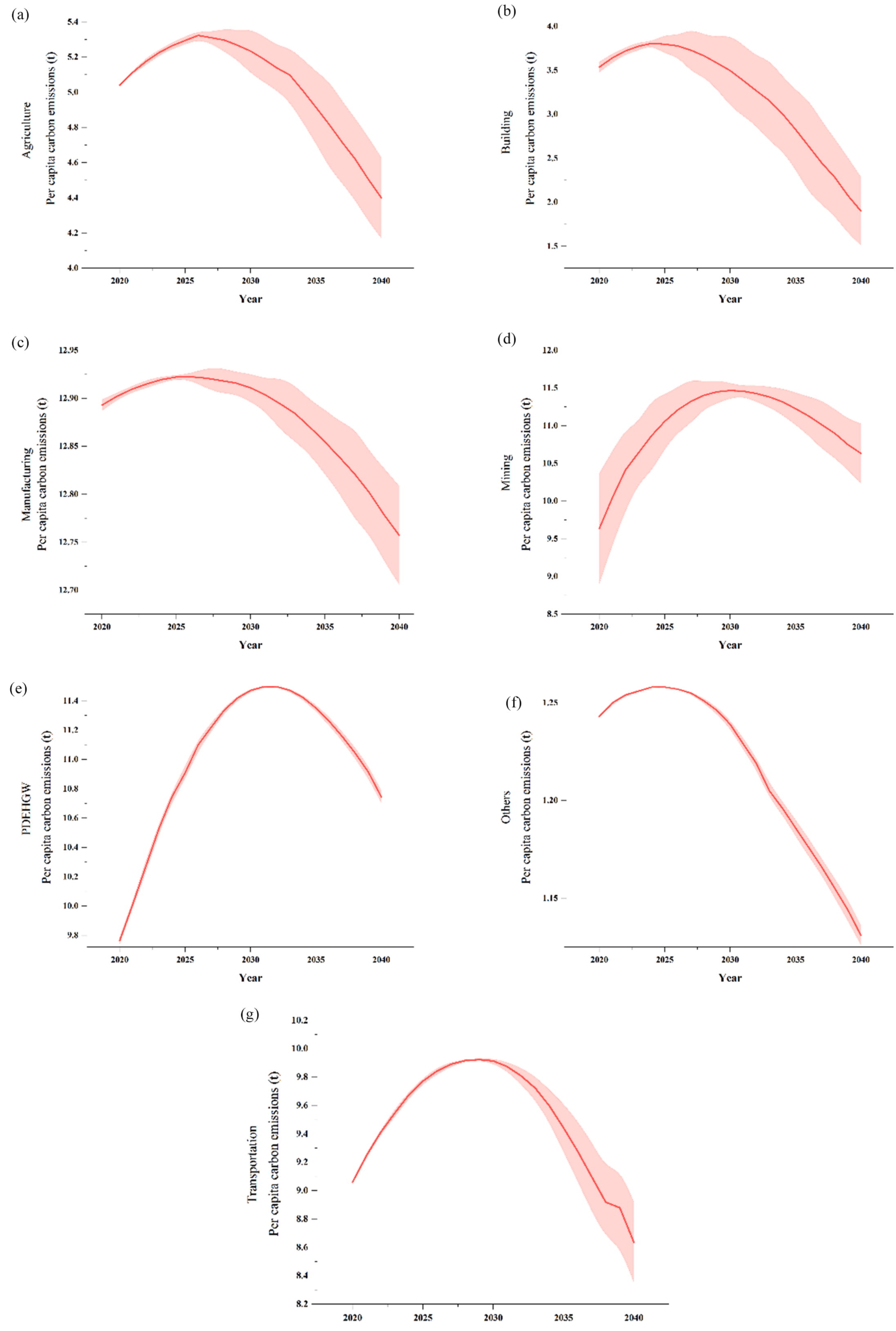

Fig. 3. Average values and 95% confidence intervals of the prediction of sectoral emissions per capita through Monte Carlo simulation (a) *Agriculture* (b) *Building* (c) *Manufacturing* (d) *Mining* (e) *PDEHGW* (f) *Others* (g) *Transportation.*

RMB) is observed in the *Others* sector, and it is 2.3 times the lowest turning point (37,281 RMB) for the *Agriculture* sector. However, this does not necessarily mean that reaching peak emissions in the *Others* sector is more complex than it is in the other cases, because the sectoral GDP per capita and its growth rates vary considerably. In 2017, for instance, the current GDP per capita of the *Agriculture* and *Others* sectors amounted to 29,650 and 39,991 RMB, accounting for 80% and 46% of the turning points, respectively. By 2030, the GDP per capita is most likely to rise to 45,972 and 64,268 RMB in the *Agriculture* and *Others* sectors, respectively. The simulation results indicate that, in all the industrial sectors, the GDP per capita will increase continuously, although the growth will decrease. This is particularly true for the *Mining* and *PDEHGW* sectors, in which the GDP per capita will increase with average annual rates of 8% and 6% between 2018 and 2024, and 6% and 4% between 2024 and 2030, respectively.

3.4. Carbon emissions projection

China's future per capita emission trajectories for all the industrial sectors, except the *Business* sector, are illustrated in Fig. 3. The results show a significant variation in the peak-reaching time and emissions among these sectors. The *Building* and *Others* sectors are expected to reach their peak emissions per capita in the period between 2021 and 2028, with the possible peak values of 3.7 and 1.25 tons, respectively. However, as GDP per capita continues to grow, the *Building* sector will experience a much more rapid decline than the *Others* sector after reaching their peak emissions. Carbon emissions per capita from the *Agriculture, Transportation*, *Manufacturing*, *PDEHGW,* and *Mining* sectors are expected to peak during the periods 2025–2032, 2025–2034, 2026–2036, 2028–2033, and 2029–2034, respectively. Nevertheless, the discrepancy in the emission trajectories and peak values between these industrial sectors seems remarkably large. The *Manufacturing*, *PDEHGW,* and *Transportation* sectors would maintain a relatively stable emission level after reaching the peak. In contrast, a relatively sharp decrease in the emissions per capita can be observed for the *Agriculture* and *Mining* sectors. Among the seven industries, the highest peak emissions per capita are found in the *Manufacturing* and *Mining* sectors at a range of 12.76–12.88 and 9.69–11.46 tons, respectively. They are followed by the *PDEHGW* and *Transportation* sectors, whose peak emissions per capita are estimated at 9.74–13.42 and 8.71–9.86 tons, respectively. The anticipated peak emissions per capita of the *Agriculture*, *Building*, and *Others* sectors appear to be much lower, ranging from 5.08 to 5.44, 1.46 to 3.71, and 1.13 to 1.26 tons, respectively.

Manufacturing, *PDEHGW*, and *Others* sectors are under more significant pressure, and they need to reach the peak emissions when the GDP per capita amounts to 71,396, 80,821, and 86,452 RMB, respectively. *PDEHGW* has a lower peak, which means that this industry should further promote low-carbon production while maintaining good economic growth. The peak GDP per capita of the *Agriculture* and *Construction* sectors is relatively low, both below 50,000 RMB. However, due to these two industries' low peak emissions per capita, the pressure to reach the peak is also more significant. The GDP per capita of the *Transportation* and *Mining* sectors reached 53,236 and 55,050 RMB, respectively, when the inflection point was reached, and the peak emissions per capita of the *Transportation* sector were relatively high; therefore, the pressure of the *Transportation* sector to reach the peak was relatively small in comparison.

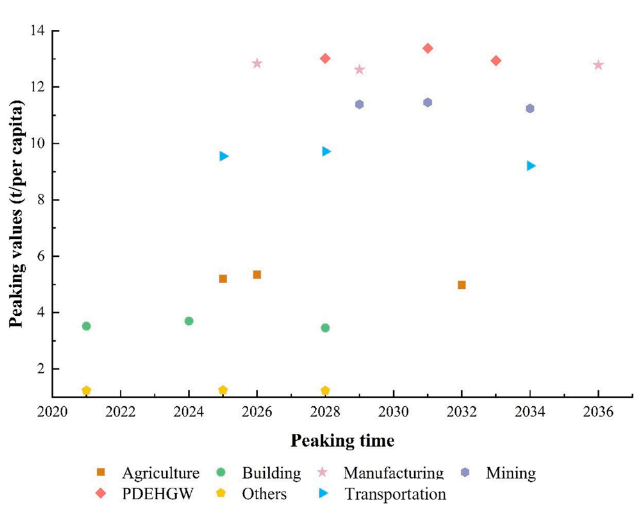

Fig. 4. Peaking time of seven industrial sectors with three scenarios.

Fig. 4 displays the earliest, latest, and most likely peaking time and values of seven sectors in total. The *Agriculture* sector is likely to peak before 2030, most likely in 2025, owing to the ever-improving technology in agricultural production [61]. The forecast results indicate that the *Building* sectors' GDP will increase rapidly between 2018 and 2023 and slowly decline between 2023 and 2025, with the peaking period ranging from 2021 to 2028, most likely in 2024, which corresponds to 3.70 tons. Meanwhile, the *Manufacturing* and *Mining* sectors will peak in the periods 2026–2036 and 2029–2034, with peaking values of 12.89 tons and 11.46 tons, respectively. Because the *Manufacturing* sector accounts for 62% of total emissions, this sector plays a crucial role in the expected peaking of emissions among all the industrial sectors [62]. Both the *Manufacturing* and *Mining* sectors have significant probabilities of peak emissions per capita before 2030. If the above two sectors could achieve a substantial reduction in emissions, China will likely become emissions free sooner than previously thought. If not, China is more likely to undergo a long-term plateau after its carbon emissions peak. The *Others* sector will peak between 2021 and 2028, most likely in 2025, with a peaking value of 1.25 tons. However, emissions from the *PDEHGW* sector will peak between 2028 and 2033, most likely in 2031, with a peaking value of 13.38 tons. The *Transportation* sector is considered as one of the fastest increasing drivers in China [63] and is predicted to peak between 2025 and 2034, most likely in 2028, with a peaking value of 9.72 tones.

4. Discussion

4.1. Comparison of projections with literature

Previous studies have increasingly focused on the pathway projections of China's peak emissions. A comparison between the peaking periods of industrial sectors in China in this study and those in previous

Table 6
Comparison of this paper with the previously researches.

Sector	Reference	Peaking year with the highest probability	The earliest peaking year	The latest peaking year
Agriculture	This paper	2026	2025	2032
	[37]		2021	2031
Building	This paper	2024	2021	2028
	[65]	2031	2027	2036
Manufacturing	This paper	2029	2026	2036
	[48]	2031	2024	2035
Mining	This paper	2031	2029	2034
	[17]	2024	2022	2029
PDEHGW	This paper	2031	2028	2033
	[83]		2023	2031
Transportation	This paper	2028	2025	2034
	[64]	2032	2026	2033

studies is provided in Table 6. As illustrated, the various sectors differ dramatically in their possible peak-reaching time.

Our prediction estimates on the *Agriculture*, *Manufacturing*, *PDEHGW*, and *Mining* sectors are generally consistent with those in the existing literature. Meanwhile, we find that it is easier for the emissions in the *Building* and *Transportation* sectors to peak, contrasting previous predictions. The most notable gaps between our estimates and those in the literature are observed in the *Transport* and *Building* sectors. Owing to the exponentially growing use of electric vehicles and low-carbon building materials in recent years, these two sectors will reach peak emissions earlier than previously thought [64–65].

Methodological differences in emission projections are probably the leading cause of the distinction between our results and those in the literature. Generally, the methods used could be divided into two types: econometrics models (e.g., EKC and Kaya identity) and the partial or general equilibrium models (i.e., computable general equilibrium (CGE) and an integrated assessment model (IAM)). Both models have strengths and weaknesses. The projections of the industrial sectors' carbon emissions face a major threat due to the high complexity and randomicity in the economic and social development [66]. Scenario settings in the existing studies usually involve a certain probability that cannot account for the stochastic uncertainties. Consequently, we employ a sophisticated technique—Monte Carlo simulation—to address the stochastic uncertainties in our emissions prediction.

4.2. Innovation and uncertainties

Compared to previous studies, this study makes three novel contributions to the literature. First, we present, for the first time, the full picture of the peaking pathways of the emissions in China's eight industrial sectors, which in aggregate made up 73% of China's total emissions in 2017. Second, in contrast to most scenario analyses that cannot account for stochastic uncertainties, we combine regression analysis and Monte Carlo simulation to examine the EKC hypothesis using probabilistic uncertainty modeling. As a result, the likely emission trajectories are predicted using probability distribution instead of fixed numbers. Third, our paper calls for a shift in the focus from China's peak emissions to the sectoral peak emissions. It proceeds with the recognition that sectors are key in making the efforts to reach peak emissions, which is largely neglected in current discourses on the pathways to peak emissions. Most studies focus on the role of heterogeneity between different regions in reaching the goal of peaking emissions by 2030, while ignoring that between different sectors [67].

Research on future peaking pathways inevitably contains uncertainties and limitations. This study attempts to conduct a preliminary survey of China's emission peaks. First, our accounting of China's carbon emissions by sector has some uncertainties [18,68–69]; however, many studies have adopted this approach broadly [68,70–71]. After comparing our estimated emissions with those by Shan et al. [11], a disagreement of less than 8% is found. Another uncertainty emanates from the variable distribution settings in our Monte Carlo simulation [72]. Studies that discuss the possible trends in these variables after the COVID-19 pandemic are scarce. Therefore, future work needs to explore how the energy and economic systems would change in the post-COVID-19 era, both on the international and intranational scales. Moreover, although Monte Carlo has so many advantages in dealing with uncertainty, in this case it does not consider the impact caused by policy change. Therefore, combining specified policy scenarios with Monte Carlo simulations would be a next step towards a more scientifically reliable analysis.

4.3. Policy implications

The COVID-19 pandemic has uncovered the fragile economic, social, and environmental underpinnings in the world. China's unprecedented lockdowns against the COVID-19 outbreak have led to a sharp decline in carbon emissions during the early months of the pandemic [73–74]. While emissions reduction is desirable, this was not the ideal means to achieve this reduction; moreover, the efforts to recover the economy may cause carbon emissions to rebound quickly in the near future [75]. Although current industrial lobbies tend to pressure the government to relax environmental regulations [76], climate actions should not take a back burner to economic recovery. The authorities should keenly observe the progress of China's NDCs and propose new industrial, financial, technological, and institutional measures [77]. Our results have the potential to inform policymakers on sector-specific policies. The *Agriculture* sector is very likely to attain peak emissions before 2030. The challenge entails preventing peak emissions per capita from being too high, and this would require a transition towards a green and modern agricultural system. The same situation applies to the *Others* sector, which is expected to peak emissions prior to 2030 with a relatively low peak-reaching value. The *Transportation* and *Building* sectors are more likely to peak emissions around 2035. The high quality peaking of emissions in the *Others* sector can be achieved through technological innovation and application; for instance, the development of new energy vehicles [77]. Regarding the *Building* sector, the share of emissions has increased, and the energy saving techniques for residential buildings should be developed [78]. The emissions in the *Manufacturing* sector, which are the highest among the eight sectors, are likely to peak between 2026 and 2036. The more emission reduction policies are implemented, the more likely the peak-reaching time will move forward. The same holds true for the *PDEHGW* and *Mining* sectors, which are supposed to reach peak emissions during the periods 2028–2033 and 2029–2034, respectively. Moreover, energy transition plays a critical role in the ongoing supply-side reform of China. A high proportion of renewables in power systems will enable an earlier peak-reaching time for these sectors [79]. Furthermore, developing countries that show continuous increases in carbon emissions play an increasingly important role in global climate mitigation [80]. In that sense, our analysis, which focuses on China—the world's largest emissions trading market and emitter of carbon emissions [81]—can serve as a reference for other countries to improve their peaking pathways from a sectoral perspective.

5. Conclusions

By tracing China's emission trajectories at the sectoral level and examining the EKC hypothesis for the eight industrial sectors, using both regression analysis and Monte Carlo simulation, we found that: (1) the *Manufacturing, Production and distributions of electricity, heat, gas, and water Transportation,* and *Mining* sectors accounted for nearly 56%, 30%, 5%, and 5% of the total emissions from the eight sectors in 2017, whereas the other four sectors collectively contributed 4%. Regarding the emissions per capita, the first two sectors remain unchanged; (2) the *Building, Production and distributions of electricity, heat, gas, and water Transportation,* and *Transportation* sectors experience fast growth in their emissions, while the proportions of the *Manufacturing* and *Mining* sectors continuously decline; (3) the *Agriculture, Building, Transportation,* and *Others* sectors may peak emissions before 2030—the *Manufacturing* and *Production and distributions of electricity, heat, gas, and water Transportation* sectors will more likely peak after 2030, and the peaking pathway of the *Business* sector remains unclear; (4) The differentiated mitigation policies based on the characteristics and dynamics of each industrial sector would be highly needed to fulfill China's latest ambitious goals to peak emissions by 2030 and even become carbon neutral by 2060; however, this analysis field is neglected in current discourses on China's peak emissions.

Future work needs to explore how the energy and economic systems would change in the post-COVID-19 era, both on the international and intranational scales. Although this paper provides novel insights into the potential pathways in which emissions peak in China by presenting a complete picture of the various sectors, rather than single ones, the peak emissions within each of the sectors should be investigated in detail. This is particularly true if the analysis aims to inform policymakers on how to maintain global warming thresholds and improve China's emission trading scheme. For example, subsectors like electricity, cement, and chemicals substantially contribute to the national emission inventory; therefore, their individual peaking pathways deserve priority attention. Currently, China's cap and trade is primarily implemented at the provincial level; therefore, studies that focus on the peaking emissions of each sector in different provinces are required [82]. Given the fundamental role of industrial sectors in achieving the Chinese Nationally Determined Contributions, it is necessary to ensure that the long-term mitigation goals of the eight sectors align with China's latest ambition to be carbon neutral by 2060. Research into China's potential peaking pathways at the sectoral level can be of global significance, as it will serve as a reference for other countries facing similar difficulties in identifying the appropriate ways of peaking sectoral emissions.

CRediT authorship contribution statement

Kai Fang: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Chenglin Li:** Data curation, Formal analysis, Writing – original draft. **Yiqi Tang:** Methodology, Data curation, Formal analysis, Writing – original draft. **Jianjian He:** Formal analysis, Visualization. **Junnian Song:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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