Socioeconomic impact assessment of China's CO_2 emissions peak prior to 2030

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Abstract: China is the largest emitter of carbon emissions in the world. In this paper, we present an Integrated Model of Economy and Climate (IMEC), an optimization model based on the input-output model. The model is designed to assess the tradeoff between emission deceleration and economic growth. Given that China's projected average growth rate will exceed 5% over the next two decades, we find that China may reach its peak CO_2 emissions levels by 2026. According to this scenario, China's carbon emissions will peak at 11.20 Gt in 2026 and will then decline to 10.84 Gt in 2030. Accordingly, approximately 22 Gt of CO_2 will be removed from 2015 to 2035 relative to the scenario wherein China's CO_2 emissions peak in 2030. While this earlier peaking of carbon emissions will result in a decline in China's GDP, several sectors, such as Machinery and Education, will benefit. In order to reach peak CO_2 emissions by 2026, China needs to reduce its annual GDP growth rate to less than 4.5% by 2030 and decrease energy and carbon intensity levels by 43% and 45%, respectively, from 2015 to 2030.

Keywords: Carbon emissions, peak, input-output, optimization model, integrated assessment model, China

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1. Introduction

In the "U.S.–China Joint Announcement on Climate Change" released in 2014, China announced that its carbon dioxide (CO_2) emissions will peak by 2030. China's CO_2 emissions through 2030 will have strong implications for the challenge of limiting temperature changes caused by anthropogenic greenhouse gas (GHG) emissions to less than 2 °C from pre-industrial levels. According to the Intergovernmental Panel on Climate Change's (IPCC) Fifth Assessment Report, the 2 °C target is likely to be achieved if atmospheric concentrations are controlled to 450 parts per million (ppm) carbon dioxide equivalent (CO_2eq) through 2100. To accomplish this, global GHG emissions need to be reduced to 30–50 GtCO_2eq by 2030 (IPCC, 2014). However, China's CO_2 emissions from fuel combustion were 8.5 Gt in 2013, accounting for a quarter of global emissions (Liu et al., 2016; Liu et al., 2015b; Yuan et al., 2016). In fact, China's carbon emissions have shown exponential growth over the past several decades and accounted for more than half of the increase in global CO_2 emissions from 1990 to 2012 (Feng et al., 2013). If China does not take measures to control GHG emissions, its CO_2 emissions may reach as high as 18 Gt by 2030 (Guan et al., 2008; Tol, 2013), in which case the global 2 °C target would be unlikely to be achieved. However, China can significantly reduce its carbon emissions if it takes measures to achieve peak CO_2 emissions levels by 2030. In this paper, we assess potential socioeconomic impacts of China's CO_2 emissions if they reach peak levels prior to 2030.

Over the past decade, numerous institutions and researchers have attempted to predict the year during which China's CO_2 emissions will peak. The most common tools used are environmental Kuznets curve (EKC) theory (Chang, 2015; Diao et al., 2009; Richmond and Kaufmann, 2006), scenario analysis (He et al., 2012; Liu et al., 2015a; Zhang et al., 2016), and the IPAT model (He, 2013; Sadorsky, 2014; Yuan et al., 2014). Based on these different methods, researchers usually get different results on the peaking time of China's CO_2 emissions. Zhang et al. (2014) used scenario analysis to research the role of technologies in CO_2 mitigation in China. They found that China's CO_2 emissions would peak by 2020 in a global carbon tax regime. He et al. (2012) proposed that China should peak its CO_2 emissions around 2030 and realize a sharp emissions mitigation by 2050. Hao and Wei (2015) used Green Solow model (GSM) to forecast the turning point in China's CO_2 emissions. The results showed that China's CO_2 emissions would peak around 2047.

However, these methods can only determine when China's CO_2 emissions will peak; they do not denote how such levels may be achieved. Therefore, we develop the Integrated Model of Economy and Climate (IMEC) based on the input-output model. In this paper, we use the IMEC model to explore whether China's CO_2 emissions will peak before 2030 and whether China will incur social costs as a result of achieving this goal.

The input-output model has been extensively used in analyses of CO_2 emissions (Mi et al., 2015a; Mi et al., 2016). Some researchers have used the input-output model to assess drivers of carbon emissions. The model is typically integrated with the structural decomposition analysis (SDA) to support the examination of emissions drivers and contributions. These drivers include gross domestic product (GDP) growth, energy efficiency, carbon efficiency, production structure, consumption structure, and population (Minx et al., 2009). China's carbon emission drivers have been quantified using this method (Su and Ang, 2012; Wei et al., 2016). Guan et al. (2008) used the input-output model to analyze drivers of Chinese CO_2 emissions and to forecast resulting carbon emissions. Their results showed that China's production-related CO_2 emissions would increase threefold by 2030.

Some scholars have used the multi-region input-output (MRIO) model to calculate consumption-based CO_2 emissions and to analyze emissions embodied in interregional or international trade (Su and Ang, 2011; Weber and Matthews, 2007; Wiedmann, 2009). Carbon emissions embodied in international trade have increased considerably over the last several decades; these emissions are exported from China and other emerging markets to developed countries. For example, Peters and Hertwich (2008) found that over 5.3 Gt of CO_2 were embodied in international trade in 2001. Davis and Caldeira (2010) showed that approximately 6.2 Gt of CO_2 emissions were traded internationally in 2004 (23% of global emissions). Peters et al. (2011) showed that carbon emissions embodied in international trade increased to 7.8 Gt of CO_2 in 2008 (26% of global emissions). Carbon leakage may also occur within a country's borders, and especially among countries exhibiting imbalanced regional development. Feng et al. (2013) tracked CO_2 emissions embodied in trade between Chinese provinces and internationally. Their results showed that 80% of carbon emissions embodied in goods consumed in highly developed coastal regions were imported from less developed Chines provinces.

2. Methodology and data

We develop an Integrated Model of Economy and Climate (IMEC), an optimization model based on the input-output model. We use the IMEC to examine socioeconomic impacts of peak Chinese emissions.

2.1 Basic linear equations of the input-output model

The input-output (IO) model is an analytical framework that was developed by Wassily Leontief in the late 1930s (Leontief, 1936). The main purpose of the input-output model is to establish a tessellated input-output table and a system of linear equations. The basic linear equations of this system are as follows:

$$(I - A) X_t = Y_t, \tag{1}$$

$$(I - A_c) X_t = V_t, \tag{2}$$

where (suppose there are n sectors in the economy) X_t is the total output vector for year t with n dimensions where x_{jt} is the output of sector j, Y_t is the final demand vector for year t with n dimensions where y_{jt} is the final demand of sector j (final demand includes consumption, capital formation and net export), V_t is the added value vector for year t with n dimensions where v_{jt} is the added value of sector j (V_t is the decision variable of the model), I is the $n \times n$ dimension identity matrix, and A is the direct requirement matrix with $n \times n$ dimensions where a_{ij} denotes direct requirements of sector i per unit of sector j output. a_{ij} is obtained from

$$a_{ij} = \frac{x_{ij}}{x_j} \quad (i, j = 1, 2, ..., n), \tag{3}$$

Where x_{ij} is the monetary value from sector i to sector j. A_c is obtained from

$$A_c = \operatorname{diag}\left[\sum_{i=1}^{n} a_{i1}, \sum_{i=1}^{n} a_{i2}, ..., \sum_{i=1}^{n} a_{in}\right], \tag{4}$$

where $\operatorname{diag}[\ ]$ is the diagonal matrix.

2.2 Setting socioeconomic constraints

2.2.1 Economic growth constraints

Climate policies may have negative impacts on social stability levels, economic development, and residential living (Guan and Hubacek, 2010). The GDP growth rate is one of the most important socio-economic indicators. Therefore, we show that the GDP growth rate is not less than λ_t in year *t*.

$$G_t = \sum_{i=1}^{n} v_{it} , \tag{5}$$

$$G_t \geq (1+\lambda_t) G_{t-1} , \tag{6}$$

where G_t is the GDP for year *t*, v_{it} is the added value of sector *i* for year *t*, and λ_t is the exogenous parameter.

2.2.2 Energy consumption constraints

Energy resources from the material basis of social development. However, supply is limited in most areas, and fossil energy combustion constitutes one of the main sources of GHG emissions. Therefore, the control of energy consumption and the promotion of non-fossil energy are essential to achieving peak carbon emissions (Ang and Pandiyan, 1997; Apergis and Payne, 2014). Therefore, it is understood that growth rates of total energy consumption are not greater than μ_{it} during year *t*.

$$E_t = \sum_{i=1}^{n} \sum_{k=1}^{m} b_{ikt} v_{it} + \sum_{k=1}^{m} E_{kt}^{h} , \tag{7}$$

$$E_t \leq (1+\mu_{1t}) E_{t-1} , \tag{8}$$

where E_t is the total level of energy consumption in year *t*, b_{ikt} denotes energy consumption *k* per unit of added value in sector *i* during year *t* (*k*=1, 2, 3, and 4 refer to coal, oil, natural gas, and non-fossil energy, respectively), E_{kt}^{h} denotes household energy consumption k for year t, and μ_{1t} is the exogenous parameter.

Carbon emissions can be effectively reduced by substituting renewable energy for fossil fuels (Cong, 2013; Cong and Shen, 2014). China ascribes great importance to the development of non-fossil energy sources, with its proportion in 2013 accounting for 9.8%. China intends to increase its share of non-fossil fuels to 15% by 2020 and to 20% by 2030 (Mi et al., 2015b; The White House, 2014).

$$\frac{E_{2030}^{r}}{E_{2030}} \geq \mu_2, \tag{9}$$

$$\frac{E_{2020}^{r}}{E_{2020}} \geq \mu_3, \tag{10}$$

where E_t^r denotes non-fossil energy consumption in year t and where μ_2 and μ_3 are exogenous parameters.

2.2.3 Emission peak constraints

To achieve peak CO_2 emissions, emission growth rates need to be controlled and must become negative following a carbon emissions peak. Therefore, it is crucial that carbon emission growth rates do not exceed φ_{1t} during year t and that $\varphi_{1t} \leq 0$ after a carbon emissions peak.

$$C_t = \sum_{i=1}^{n}\left(\sum_{k=1}^{m} d_{ik}E_{ikt} + s_i v_{it}\right) + C_t^h, \tag{11}$$

$$C_t \leq \left(1+\varphi_{1t}\right)C_{t-1}, \tag{12}$$

$$\varphi_{1t} \leq 0, \text{ if } t \geq \bar{t}, \tag{13}$$

where C_t denotes CO_2 emissions for year t, d_{ik} denotes CO_2 emissions per unit of energy consumption k in sector i, E_{ikt} denotes energy consumption k in sector i during year t, s_i denotes non-energy related CO_2 emissions per unit of added value in sector

i, C_t^h denotes household CO_2 emissions for year t, $\bar{t}$ denotes the year of the carbon emissions peak, and φ_{1t} is an exogenous parameter. In addition, China plans to decrease CO_2 emissions per unit of GDP from 2005 levels by 40–45% and 60–65% by 2020 and 2030, respectively.

$$\frac{C_{2020}}{G_{2020}} \leq \left(1-\varphi_2\right)\frac{C_{2005}}{G_{2005}}, \tag{14}$$

$$\frac{C_{2030}}{G_{2030}} \leq \left(1-\varphi_3\right)\frac{C_{2005}}{G_{2005}}, \tag{15}$$

where φ_2 and φ_3 are exogenous parameters.

2.2.4 Employment constraints

Employment is one of the most important issues related to macroeconomic planning. To control the unemployment rate, the growth rate of employment opportunities must not fall below the population growth rate.

$$P_t = \sum_{i=1}^{n} q_i v_{it}, \tag{16}$$

$$\frac{P_t - P_{t-1}}{P_{t-1}} \geq \frac{L_t - L_{t-1}}{L_{t-1}}, \tag{17}$$

where P_t denotes employment opportunities for year t, q_i denotes employment opportunities per unit of added value in sector i, and L_t denotes the population in year t.

2.2.5 Industrial structure change constraints

Each industry performs irreplaceable functions in an economic system, and industrial structures cannot be adjusted freely over a period of time (Mi et al., 2015a). Therefore, the lower and upper bounds of proportions of sectoral added value in GDP are constrained in the model.

$$\frac{v_{it}}{G_t} \geq (1+\alpha_{it})\frac{v_{i,t-1}}{G_{t-1}}, \tag{18}$$

$$\frac{v_{it}}{G_t} \leq (1+\beta_{it})\frac{v_{i,t-1}}{G_{t-1}}, \tag{19}$$

where v_{it} denotes the added value of sector *i* in year *t*, G_t denotes the GDP for year *t*, and α_{it} and β_{it} are exogenous parameters. Proportions of sectoral value in GDP are used as control variables in this model.

2.2.6 Consumption and investment constraints

Final demand consists of consumption, capital formation, and net export:

$$y_{it} = q_{it} + f_{it} + o_{it}, \tag{20}$$

where y_{it}, q_{it}, f_{it} and o_{it} denote final demand, consumption, capital formation, and net exports for year *t*, respectively. For each sector, wherein proportions of consumption, capital formation, and net export are assumed to be constant:

$$\frac{q_{it}}{y_{it}} = \frac{q_{i0}}{y_{i0}} \quad (i = 1, 2, ..., n), \tag{21}$$

$$\frac{f_{it}}{y_{it}} = \frac{f_{i0}}{y_{i0}} \quad (i = 1, 2, ..., n), \tag{22}$$

$$\frac{o_{it}}{y_{it}} = \frac{o_{i0}}{y_{i0}} \quad (i = 1, 2, ..., n), \tag{23}$$

where y_{i0}, q_{i0}, f_{i0} and o_{i0} denote final demand, consumption, capital formation, and net exports for the base year, respectively. The lower and upper bounds of consumption rates are constrained in the model:

$$Q_t = \sum_{i=1}^{n} q_{it}, \tag{24}$$

$$\frac{Q_t}{G_t} \geq \gamma_1, \tag{25}$$

$$\frac{Q_t}{G_t} \leq \gamma_2, \tag{26}$$

where Q_t denotes consumption in year *t*, and γ_1 and γ_2 are exogenous parameters.

2.3 Setting objective functions

Objective functions are key elements in optimization models. Typically, various modelers choose different objective functions (Daly et al., 2015; Humpenöder et al., 2015). Objectives of the climate change integrated assessment model (IAM) can be divided into welfare maximization and cost minimization goals (Wei et al., 2015; Wei et al., 2013; Yang et al., 2016). The IMEC uses the former and maximizes the sum of present values of intertemporal national welfare. We define individual welfare as the logarithm of per capita consumption, which has been widely used in modern theories of optimal economic growth (Cass, 1965; Ramsey, 1928). Therefore, the objective function is:

$$\text{Max} \sum_{t=1}^{T} L_t \log\left(\frac{Q_t}{L_t}\right)\frac{1}{\left(1+\rho\right)^{t-1}}, \tag{27}$$

where ρ is the pure rate of time preference, T is the number of years, L_t is the population in year *t*, and Q_t denotes consumption in year *t*.

2.4 Data sources

The data used in this study were primarily obtained from the World Input–Output Database (WIOD) (Timmer et al., 2015). More specifically, the Chinese input-output table used was drawn from WIOD National Input-Output Tables, energy and carbon emissions data were drawn from WIOD Environmental Accounts, and employment dates and price levels of added value were drawn from WIOD Socio Economic Accounts. In addition, population data were drawn from United Nations World population prospects: the 2012 revision (United Nations, 2013). Key 2009 data for China are shown in the Appendix A.

3. Scenario design

3.1 Economic growth

China's economy has enjoyed rapid growth. The average annual GDP growth rate has been 9.5% over the past two decades. In addition, China's annual GDP growth rate has shown a clear downward trend. The country's GDP growth rate increased from 1998 to 2007, peaking at 14.2% in 2007. It then decreased to 7.4% in 2014. It is very likely that China's GDP growth will continue to decrease over the next two decades. The lower bound of the country's GDP growth rate is currently 7% (2015) and will decrease by 0.2% each year until 2035. As a result, the lower bound of the average annual GDP growth rate will remain at approximately 5% from 2015 to 2035.

3.2 Energy consumption and fuel mix

Coinciding with its rapidly growing economy, China's energy consumption has also increased dramatically (Timmer et al., 2015). The growth rate peaked at 17.5% in 2004 and then decreased each year thereafter. Therefore, the upper bound of energy consumption growth is 5.9% as of 2015 and will decrease by 0.1% each year until 2035.

China's non-fossil fuel sectors have developed rapidly; the proportion of non-fossil fuels used in primary energy consumption increased from 6.1% in 1995 to 9.8% in 2013. According to China's Energy Development Strategy Action Plan (2014-2020), the share of non-fossil fuels is projected to reach 15% by 2020 (State Council, 2014).

In the U.S.–China Joint Announcement on Climate Change, China also announces that it will increase its consumption of non-fossil fuels to 20% by 2030 (The White House, 2014).

3.3 Carbon emission peak

The upper bound of China's CO_2 emissions growth rate is assumed to decline linearly. The upper bound of its growth rate was 6% in 2010, as the average growth rate of China's CO_2 emissions was approximately 6% from 1995 to 2009 (Timmer et al., 2015). As is well known, the CO_2 emissions growth rate should be negative following a carbon emissions peak. If China's CO_2 emissions peak in year $\bar{t}$, we assume that the upper growth rate bound will be -0.5% in year $\bar{t}+1$. The upper bounds for other years are calculated using the linear assumption. For instance, if China's CO_2 emissions peak in 2030, the upper bound of growth rate will be -0.5% in 2031. Thus, the upper bound of the CO_2 emissions growth rate declines by approximately 0.3% per year.

In addition, we examine non-energy-related CO_2 emissions for each sector. Non-energy emissions per unit added value in each sector have not varied significantly over the past two decades. Therefore, we assume that non-energy CO_2 emissions per unit added value to be equal to 2014 levels until 2035.

3.4 Technological change

In this paper, technological change is denoted as the reduction in energy intensity levels (energy consumption per unit of added value or GDP) in each sector. All sectors were divided into two categories when energy intensity levels were set. In the first category, energy intensity levels have reduced dramatically over the past two decades. Thus, energy intensity levels are predicted to decline exponentially until 2035. For example, energy intensity levels of the Education (S31) sector decreased from 8.15

MJ/US$ in 1995 to 1.47 MJ/US$ in 2014 (Timmer et al., 2015). The R^2 value of its exponential regression is 0.97. According to the exponential assumption, this value will decline to 0.86 MJ/US$ in 2020 and to 0.35 MJ/US$ in 2030 (Timmer et al., 2015). For the second category, energy intensity has fluctuated over the past two decades. Thus, it is assumed that energy intensity levels will be equal to the average value for 1995–2014 until 2035. For example, energy intensity levels of the Air Transport (S24) sector have fluctuated between 45 and 100 MJ/US$ over the past two decades with an average level of 66 MJ/US$. Therefore, we assume that this will remain at 66 MJ/US$ until 2035.

3.5 Industrial structure change

The proportions of sectoral added value to GDP are the control variables of the IMEC model. The proportion of sectoral added value in GDP is assumed to change each year under upper and lower bound constraints. According to historical data, the upper bound is 4.5% as of 2015 and will increase by 0.5% each year until 2035. Meanwhile, the lower bound is -4.5% as of 2015 and will decrease by 0.5% each year until 2035.

4. Results

4.1 The path to China's carbon peak

There is a tradeoff between GDP growth and carbon emissions reduction. In this study, the lower bound of the average annual GDP growth rate is predicted to remain at approximately 5% from 2015 to 2035. Under this constraint, China may experience a peak in carbon emissions by 2026. From objectives to maximize social welfare, an optimal pathway is obtained. First, China's CO_2 emissions will peak at 11.20 Gt in 2026 according to this scenario, and cumulative emissions from 2015 to 2035 are estimated to reach 219.72 Gt (Figure 1). China's average annual CO_2 emissions growth rate was 5.18% from 1995 to 2014, and this value will decrease to 1.33% from 2015 to 2030 if

China’s CO_2 emissions peak in 2026.

Second, the annual GDP growth rate will decline to less than 4.5% by 2030. Energy is essential to economic development, and energy combustion serves as one of the main sources of carbon emissions. Thus, GDP growth has a dramatic effect on CO_2 emissions (Peters et al., 2007). China’s economy has experienced rapid development over the past several decades. The average annual GDP growth rate was approximately 9.5% from 1995 to 2014. However, this GDP growth rate must be reduced in order to reach peak CO_2 emissions by 2026.

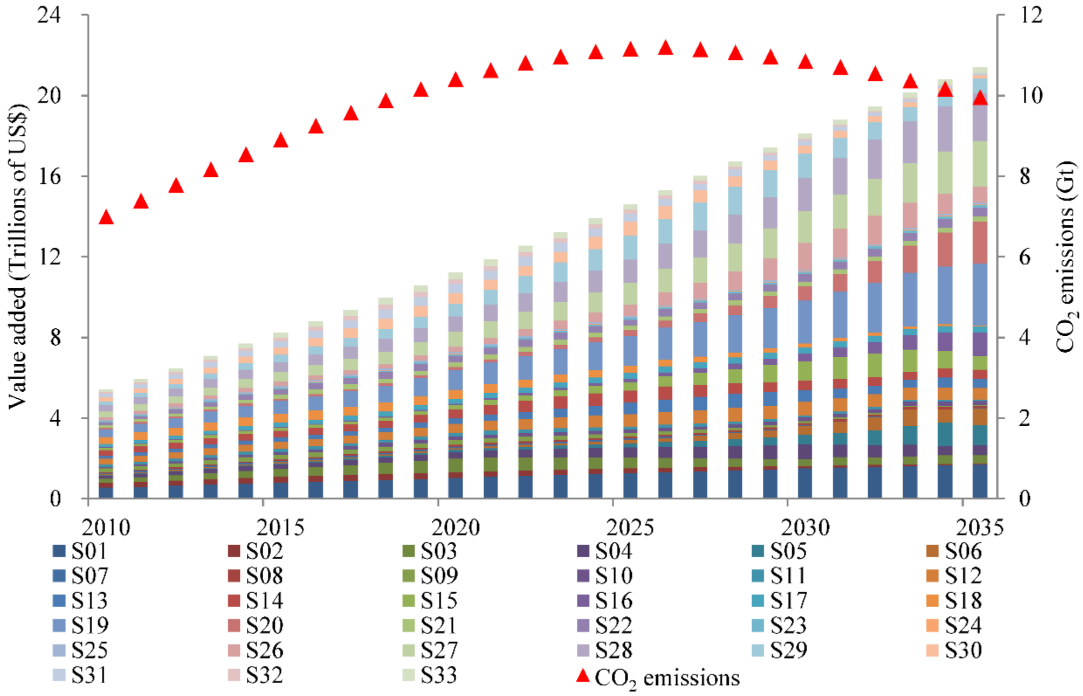

Figure 1. Optimal pathways of CO_2 emissions and GDP based on a scenario wherein CO_2 emissions peak in 2026. S01–S33 are sector codes; for full names, see Appendix A.

Third, tertiary industries will increase while secondary industries will decline. More specifically, according to this scenario, the proportion of tertiary industrial activities increases from 47.57% in 2014 to 57.46% in 2030 while by contrast, the proportion of secondary industrial activities declines from 42.67% in 2014 to 34.22%

in 2030. In fact, the energy intensity of secondary industrial activities for 2014 is reported as 42.37 MJ/US$, which is approximately 14 times more than that recorded for tertiary industrial activities. Therefore, carbon emissions can be effectively controlled via tertiary industry promotion.

According the sectoral perspective, added value to sectors with relatively low levels of energy intensity will grow quickly. The following three sectors will have the highest proportion of added value in GDP in 2030: Wholesale Trade and Commission Trade (S19), Real Estate Activities (S28), and Financial Intermediation (S27). Their proportions will be 11.79%, 9.16%, and 8.70% in 2030, respectively, and their average annual growth rates will exceed 8% from 2015 to 2030. By contrast, added value to several sectors of relatively high levels of energy intensity will gain smaller proportions of GDP. These sectors include the following: Pulp, Paper, Printing and Publishing (S07); Chemicals and Chemical Products (S09); and Mining and Quarrying (S02).

Fourth, China needs to control the total energy consumption and increase the share of non-fossil energy use in order to achieve peak carbon emissions by 2026. Energy consumption and carbon emissions levels are directly related, and thus a carbon peak will constrain growth in energy use. The average annual growth rate of Chinese energy consumption was 5.87% from 1995 to 2014, and this value will be reduced to 1.46% from 2015 to 2030 if China's CO_2 emissions peak in 2026.

Fifth, China's energy intensity and carbon intensity levels will decline dramatically. China's GDP will grow by more than 110%, and its energy consumption and CO_2 emission levels will increase by 24% and 22%, respectively. As a result, energy and carbon intensity levels will decline by 43% and 45%, respectively (Figure 2).

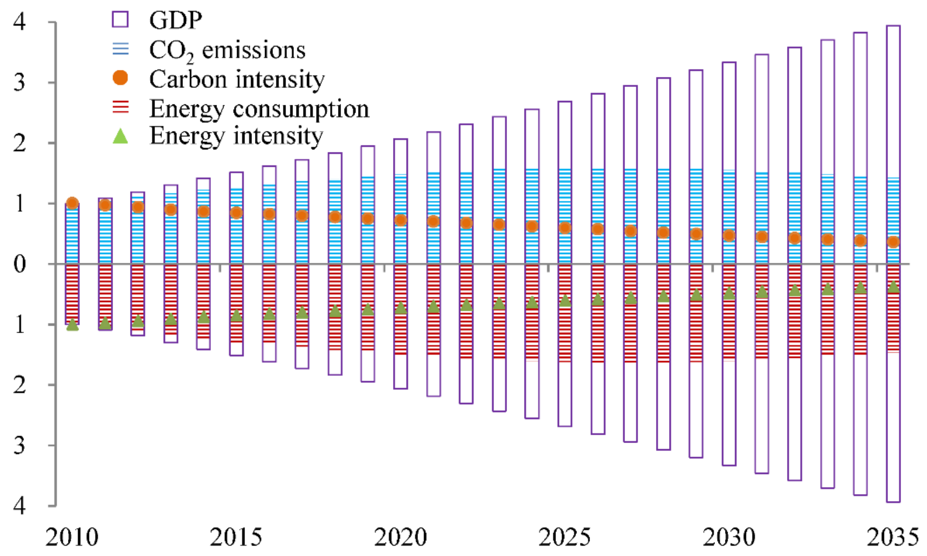

Figure 2. China's energy and carbon intensity levels will decline dramatically. Levels for 2010 are set to 1 for all indicators.

According to the sectoral perspective, most sectoral energy and carbon intensity levels will also decline (Figure 3). Figures 3(a) and 3(b) show energy consumption levels of each sector for 2014 and 2030, respectively. The horizontal axis shows the accumulated value added, and the vertical axis presents energy intensity levels. The total area refers to the consumption of different forms of energy. It is evident that sectoral energy intensity levels will decline considerably. In addition, the share of coal in total energy consumption will decline, as the red area of 2030 is much smaller than that of 2014. Figures 3(c) and 3(d) show carbon emissions of each sector for 2014 and 2030, respectively. Sectoral energy intensity levels will also decline considerably. Non-energy related emissions are primarily derived from the production of Basic Metals and Fabricated Metals (S12) and Other Non-Metallic Minerals (S11).

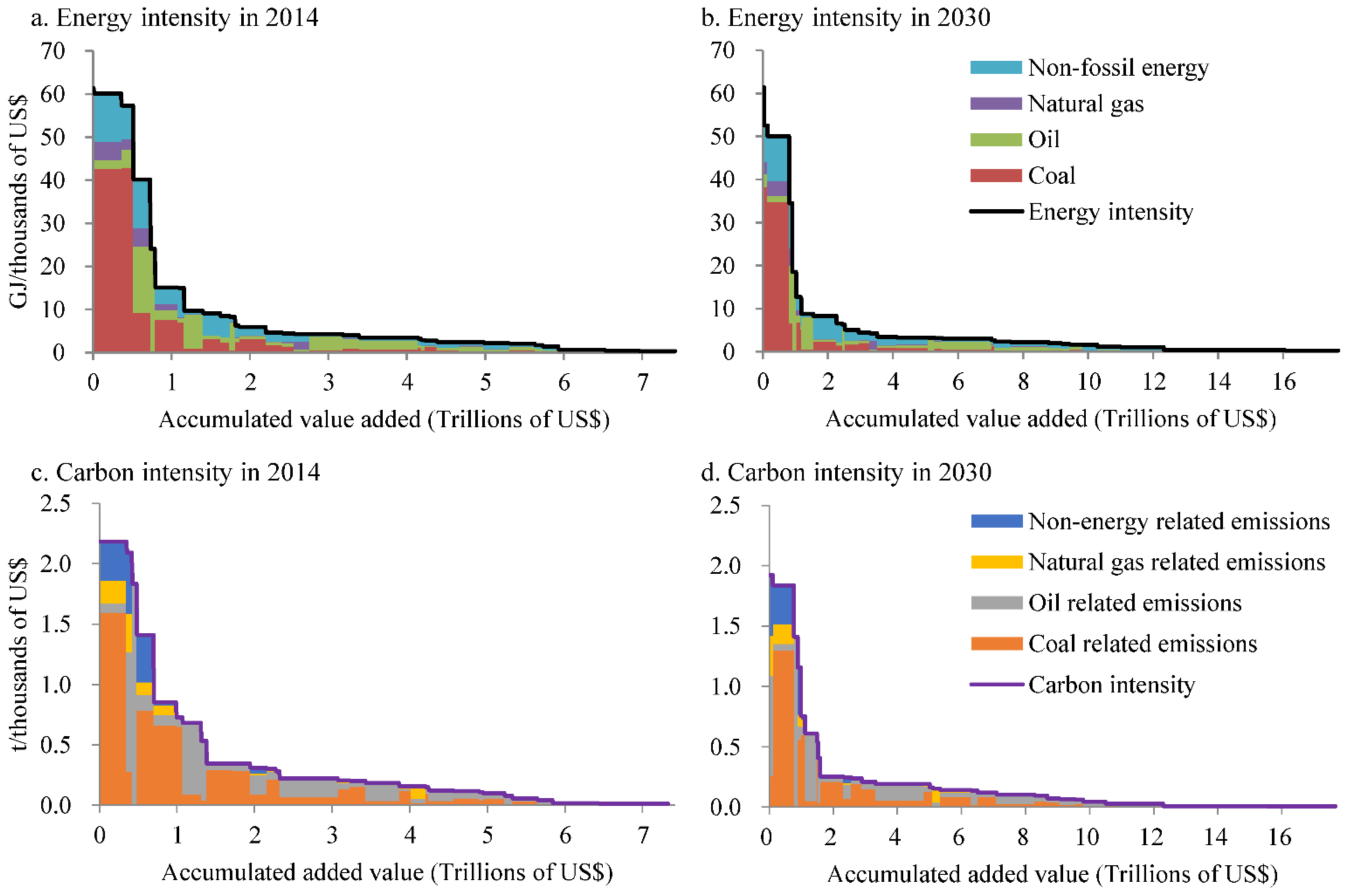

Figure 3. Energy and carbon intensity levels in most sectors will decline. (Note: Energy consumption levels for S08 and S17 are not shown, as energy intensity levels in these sectors are much higher than those of other sectors. In addition, carbon emissions for S11, S17 and S24 are not shown, as carbon intensity levels in these sectors are much higher than those of other sectors.)

4.2 Socioeconomic impacts of an earlier Chinese carbon emissions peak

CO_2 emission peaks constrain national economic growth and energy consumption, thus affecting socio-economic systems. We assess optimal pathways whereby CO_2 emissions peak in different years from 2026 to 2030. Figure 4 compares carbon emissions and GDP levels under different scenarios. The scenario wherein CO_2 emissions peak in 2030 is designated as a business as usual (BAU) case.

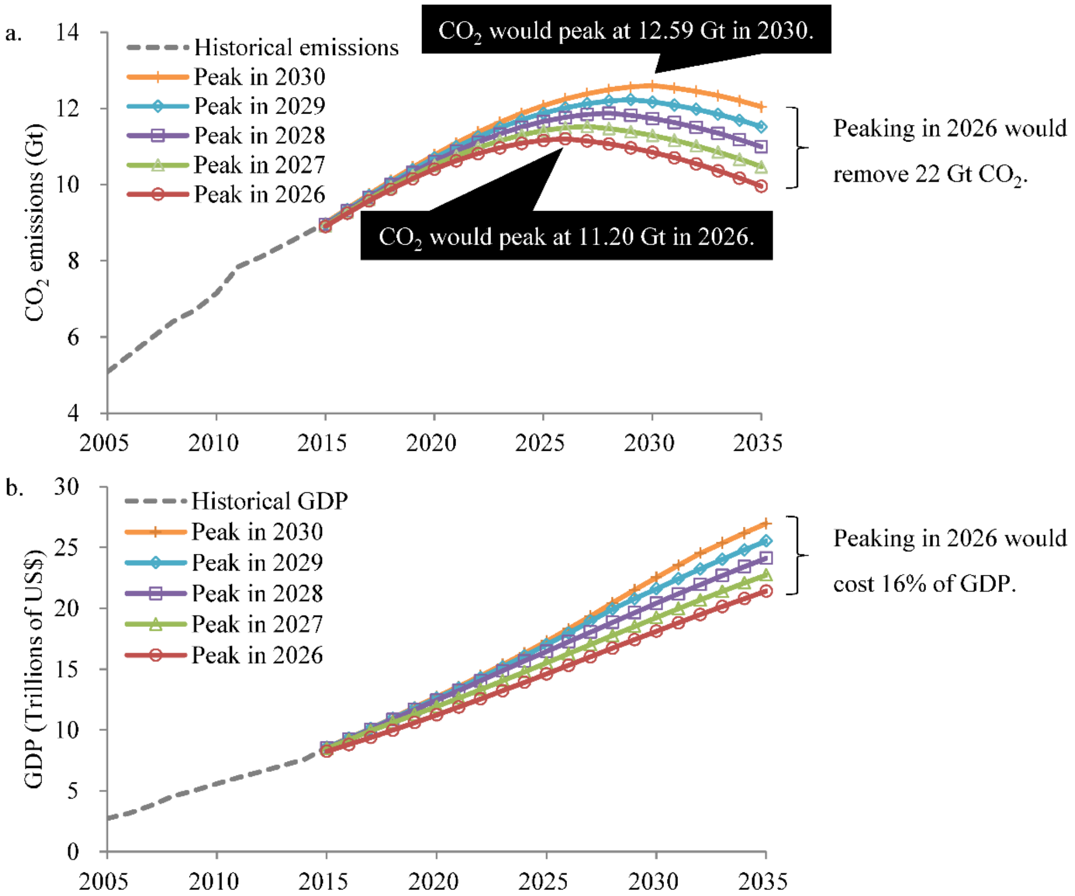

Figure 4. If China's CO_2 emissions peak in 2026, approximately 22 Gt of CO_2 will be removed from 2015 to 2035 relative to the scenario wherein China's CO_2 emissions peak in 2030.

As shown in Figure 4a, China's carbon emissions will peak at 12.59 Gt in 2030 under the BAU. According to the IPCC's Fifth Assessment Report, Global GHG emissions need to be reduced to between 30 and 50 Gt by 2030 for the 2 °C target to be reached (IPCC, 2014). The BAU scenario thus does not achieve the 2 °C target. However, carbon peak values will be much lower if CO_2 emissions peak sooner. The turning point of China's carbon emissions would be reduced to 11.20 Gt if the country's CO_2 emissions were to peak in 2026. As a result, approximately 21.64 Gt of CO_2 would be removed from 2015 to 2035.

Figure 4b shows GDP levels under different scenarios. The earlier China's CO_2 emissions peak, the greater the country's GDP loss. Early carbon emissions peaking can cause a dramatic reduction in total CO_2 emissions and GDP (Table 1). According to the BAU scenario, China's cumulative CO_2 emissions and GDP will be 241.26 Gt and 369.17 trillion US$, respectively, from 2015 to 2035. If China's CO_2 emissions peak before 2030, CO_2 emissions will be reduced by 2.07–8.93%, and 2.93–16.45% of GDP will be lost.

Table 1. Cumulative carbon emissions and GDP under different scenarios

Peak year	Cumulative CO_2 emissions (Gt)	Cumulative GDP (Trillions of US$)	CO_2 reduction (%)	GDP loss (%)
2030	241.26	369.17	–	–
2029	236.26	358.35	2.07	2.93
2028	230.97	344.43	4.27	6.70
2027	225.37	327.13	6.58	11.39
2026	219.72	308.43	8.93	16.45

Note: Cumulative CO_2 emissions and GDP accumulated from 2015 to 2035. The scenario wherein carbon emissions peak in 2030 is used as the BAU for calculating CO_2 emission reduction and GDP decline.

Earlier carbon emissions peaking will benefit several sectors. Relative to the BAU scenario, the added value to most sectors will be reduced if China's carbon emissions peak in 2026. The added value to the Food, Beverages and Tobacco (S03); Pulp, Paper, Printing and Publishing (S07); and Retail Trade and Repair of Household Goods (S20) industries would decline by approximately 60%. However, several sectors would benefit from an earlier carbon emissions peak, as added value to the Machinery, not elsewhere classified (S13); Renting of Machinery and Equipment and Other Business Activities (S29); and Education (S31) sectors would grow by 106%, 56%, and 29%, respectively.

4.3 Uncertainty analysis

Uncertainty exists in the input-output modeling method. The optimization model used in this study is based on the static input-output model. Thus, interdependencies between different sectors of China's economy are held constant. For a discussion of input-output model uncertainty, see Wiedmann (2009) and Peters et al. (2007). The dynamic input-output model, which reflects inter-sectoral balancing over time, can be used to deal with this uncertainty in future work.

In addition to the uncertainty in methodology, the assumptions in the scenario design are also controversial. For example, we assume that China's average annual GDP growth rate will exceed 5% from 2015 to 2035. This assumption is based on China's current economic situation and government planning, which affect the results. If the lower bound of GDP growth is reduced, China may reach peak CO_2 emissions sooner. The sensitivity analysis is carried out on the exogenous parameters, such as lower bound of GDP growth, upper bound of energy consumption, upper bound of carbon emission, technological change, and population. The Figure 5(a) and 5(b) show the impacts on GDP and CO_2, respectively, when the exogenous parameters change by 5% or -5%. The most sensitive assumption is technological change, while population does not have impacts on the results.

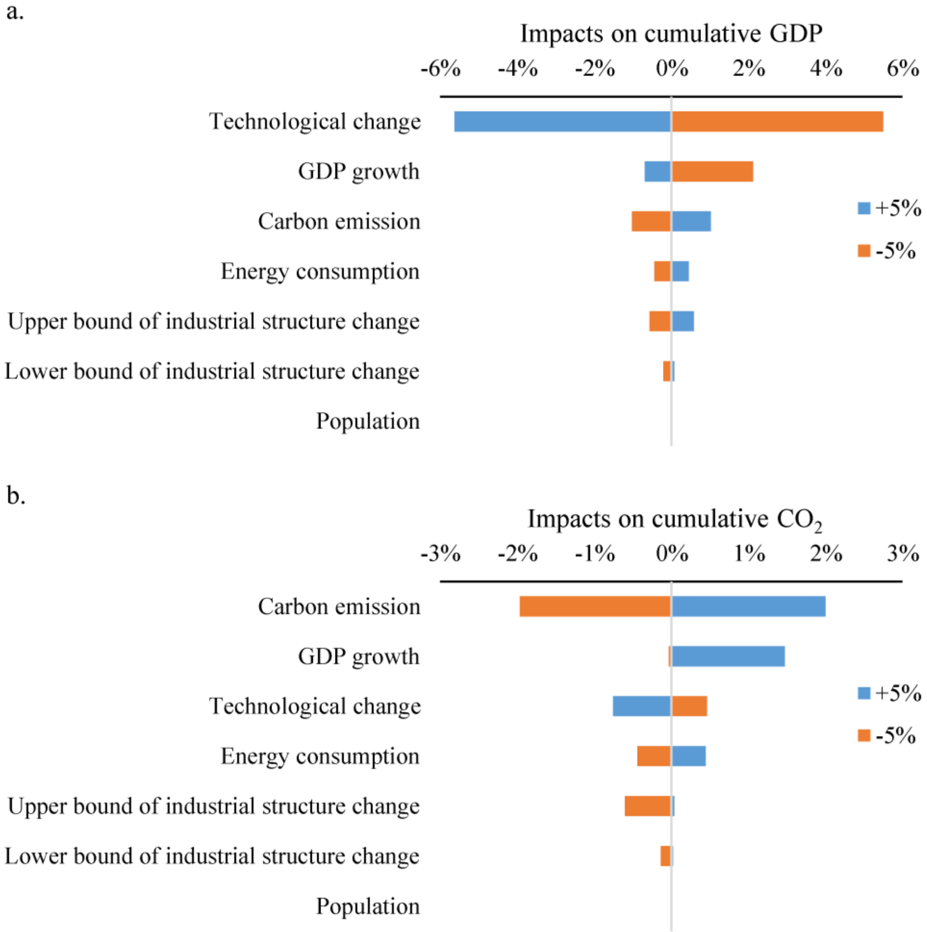

Figure 5. Impacts on GDP and CO_2 of exogenous parameters.

Finally, data uncertainty may be significant. Several authors have questioned Chinese energy and carbon data (Guan et al., 2012; Liu et al., 2015b). Liu et al. (2015b) revealed that energy consumption in China was underestimated by the Chinese national statistics while its carbon emission was overestimated by IPCC and other reports. In addition, we mainly use energy and economic data of WIOD and design scenarios based on the Chinese government planning and data from Chinese national statistics. The gap between WIOD data and Chinese national statistics may also affect the results.

5. Conclusions

Currently, China emits approximately 25% of global CO_2 emissions. With the dramatic growth in China's carbon emissions, this percentage is on the rise. Thus, China's carbon emissions plan will have strong implications for global mitigation. China has promised to peak its carbon emissions by 2030, but this target will not achieve the 2 °C target. We find that China may peak its CO_2 emissions by 2026 if its average annual GDP growth rate exceeds 5% from 2015 to 2035. According to this scenario, China's carbon emissions will peak at 11.20 Gt in 2026 and will drop to 10.84 Gt in 2030. Accordingly, approximately 22 Gt of CO_2 will be removed from 2015 to 2035.

An earlier carbon emissions peak would benefit several sectors. If China's carbon emissions were to peak in 2026, its cumulative GDP would be reduced by 16.45%, and this would in turn reduce the added value to most sectors. However, several sectors would benefit from an earlier carbon emissions peak (e.g., Machinery and Education).

Based on the results of this study, we present several suggestions on ways in which China may peak its CO_2 emissions prior to 2030. First, China needs to set total carbon emissions targets. The Chinese government has announced a reduction in carbon intensity from 2005 levels of 40–45% by 2020 and by 60–65% by 2030. These are both emission-intensity targets. Two main approaches are used to lower carbon intensity levels: reducing carbon emissions and increasing GDP. Most regions in China prefer the latter, as economic development constitutes one of the most important criteria used to promote provincial and local leaders. Therefore, Chinese government should set up a balanced policy, which considers the economic development, environmental protection and social cohension (Cong and Brady, 2012). We find that China must reduce its GDP growth rate to less than 4.5% by 2030 in order to achieve peak CO_2 emissions by 2026.

Second, China needs to update its industrial structure. Over the past few decades, China's economic growth has been based on the development of heavy industry and manufacturing. China has become a 'factory to the world' owing to its access to low-cost labor, land, and resources. In 2014, the energy intensity of China's secondary industry was approximately 15 times that of its tertiary industry. Therefore, carbon emissions can be effectively controlled through tertiary industry promotion. China needs to develop low-carbon industries (e.g., Wholesale and Commission Trade, Real Estate Activities, and Financial Intermediation).

Third, total energy consumption levels, and coal consumption levels in particular, must be reduced. China has set targets to lower total primary energy consumption to under 4.8 billion tons of standard coal equivalent and to reduce the proportion of coal consumption to under 62% by 2020. These targets will not allow China to achieve peak carbon emissions by 2026. Our results show that China needs to control total energy consumption more strictly in order to achieve peak carbon emissions by 2026.

Fourth, technological change will play a critical role in China's achievement of peak carbon emissions prior to 2030. Technological change constitutes one of the most important drivers of CO_2 emissions reduction (Guan et al., 2008). This paper shows that China's energy and carbon intensity levels will decline by 43% and 45%, respectively, if its CO_2 emissions peak in 2026.

However, this paper has limitations. First, there are uncertainties in exogenous parameters. The sensitivity analysis is carried out on key exogenous parameters, such as lower bound of GDP growth, upper bound of energy consumption, upper bound of carbon emission, technological change, and population. Recently, many researchers have proposed to include endogenous technological change in models. For example, Acemoglu et al. (2012) introduced endogenous and directed technological change in a growth model with environmental constraints. Second, the interactions between production sectors and final demand are not taken into considerations. Computable general equilibrium (CGE) model is a potential method to solve this issue. Classical CGE model will be considered to research the future pathways of China's CO_2 emissions. Third, technological breakthroughs (e.g., carbon capture and storage (CCS)) are not considered in this paper. CCS has great potential to reduce CO_2 emissions, as new technologies can substantially reduce its costs (Yu et al., 2016). We thus plan to analyze more scenarios that consider new technological breakthroughs.

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Appendix A. Key 2009 socio-economic system, energy, and carbon emissions data for China

Code	Sector	Output	Added value	Final demand	Number of employees	Coal consumption	Oil consumption	Natural gas consumption	Non-fossil energy consumption	CO_2 emissions
		Billions of US$, 2009	Billions of US$, 2009	Billions of US$, 2009	Million	PJ	PJ	PJ	PJ	Mt
S01	Agriculture, Hunting, Forestry and Fishing	880	517	248	273	348	1151	0	354	118
S02	Mining and Quarrying	466	218	-152	11	1701	579	324	676	195
S03	Food, Beverages and Tobacco	779	191	333	16	666	114	18	376	71
S04	Textiles and Textile Products	651	135	231	20	459	115	6	653	50
S05	Leather, Leather and Footwear	136	27	64	7	16	32	3	35	4
S06	Wood and Products of Wood and Cork	177	40	7	10	106	38	3	109	12
S07	Pulp, Paper, Printing and Publishing	237	58	-4	11	512	60	6	364	52
S08	Coke, Refined Petroleum and Nuclear Fuel	257	48	-9	1	4232	16271	307	438	101
S09	Chemicals and Chemical Products	806	170	-11	9	1985	2353	639	1840	269
S10	Rubber and Plastics	349	67	37	12	197	71	6	306	23
S11	Other Non-Metallic Mineral	402	111	14	9	5244	446	189	777	712
S12	Basic Metals and Fabricated Metal	1321	269	32	10	12629	522	1091	3098	628
S13	Machinery, Nec	680	159	276	12	336	129	30	287	39
S14	Electrical and Optical Equipment	1446	246	455	18	124	110	24	330	19
S15	Transport Equipment	563	112	249	7	180	90	44	228	25
S16	Manufacturing, Nec; Recycling	85	32	53	8	43	23	1	38	6

S17	Electricity, Gas and Water Supply	482	138	21	4	35277	295	683	5617	3326
S18	Construction	1417	330	1371	79	189	1285	5	159	71
S19	Wholesale Trade and Commission Trade	585	352	235	18	30	67	1	209	8
S20	Retail Trade; Repair of Household Goods	121	73	49	48	6	87	0	44	7
S21	Hotels and Restaurants	277	105	97	23	29	68	251	168	22
S22	Inland Transport	270	140	36	19	133	1140	16	120	98
S23	Water Transport	109	49	32	2	0	1313	0	0	100
S24	Air Transport	44	11	10	1	0	1093	0	0	78
S25	Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies	111	43	17	3	23	382	2	7	31
S26	Post and Telecommunications	210	125	80	9	3	73	0	108	6
S27	Financial Intermediation	376	260	77	5	0	42	0	71	3
S28	Real Estate Activities	328	273	237	2	6	45	0	31	4
S29	Renting of Machinery and Equipment and Other Business Activities	454	186	70	4	107	175	45	128	26
S30	Public Admin and Defence; Compulsory Social Security	342	188	327	16	142	144	29	124	26
S31	Education	283	159	237	23	124	97	1	199	19
S32	Health and Social Work	241	83	206	8	189	33	16	97	23
S33	Other Community, Social and Personal Services	266	120	107	109	123	273	39	78	39
	Final household consumption expenditures	–	–	–	–	1931	3592	751	10920	482
	Grand total	**15150**	**5033**	**5033**	**809**	**67090**	**32308**	**4530**	**27992**	**6696**

Note: PJ denotes 10^{15} joules, and Mt denotes 10^{6} tons.

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