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Assessing the “negative effect” and “positive effect” of COVID-19 in China

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A B S T R A C T

The COVID-19 pandemic lockdowns led to a sharp drop in socio-economic activities in China in 2020, including reductions in fossil fuel use, industry productions, and traffic volumes. China’s economy suffered a serious negative effect from COVID-19. However, there is a “positive effect” on CO2 emissions reduction. Here, for the first time, this paper constructs a new model named “Weighted Multi-regional Hypothetical Extraction Method (WMHEM)” based on a multi-regional input-output model. It not only solves the problems of traditional HEM methods such as improper use of assumptions, excessive reliance on industry intermediate input, but also accurately reflects the impact of external shocks on the inter-industry linkages. By using the monthly economic data of each provinces in China during COVID-19 (except Hong Kong, Macao and Taiwan) an the latest Multi-regional input-output tables, the “economic negative effect” and “CO2 emission positive effect” under COVID-19 in China are measured. Results show that COVID-19 lockdown was estimated to have reduced China’s CO2 emissions substantially between January and March in 2020, with the largest reductions in February. With the spread of coronavirus controlled, China’s CO2 emissions rebounded in April. In addition, key emission reduction sectors and key development encouraged sectors are selected by combining “economic negative effect” and “CO2 emission positive effect” during COVID-19. Therefore, policies recommendations are put forward based on forward and backward linkages respectively which are from two ends of the supply chain to turn pandemic-related CO2 emissions declines into firm climate action.

1. Introduction

China responded to the outbreak of COVID-19 in 2019 in Wuhan City by enforcing restrictions on mobility and activity. The actions, including social distancing, a travel ban, closing down non-essential local business and the lockdown of most commercial and industrial activities, have led the global economy into one of its most severe recessions since 1900 (Anderson et al., 2020; Hellewell et al., 2020; Le Quéré et al., 2020), and China’s gross domestic product (GDP) dropped by 6.8% in the first quarter of 2020, compared with the same period in the previous year as shown in Fig. 1 (NBS, 2020). The “economic negative effect” of COVID-19 pandemic began to be analyzed by some researchers (Al-Baidhani, 2020; Md and Rahaman, 2021; Zhang, Y. et al., 2020).

However, the pandemic and lockdown policies not only affect production activities but also lead to substantial changes in people’s lifestyles and energy consumption amount, and can also bring about the “CO2 emission positive effect” (Sarfraz et al., 2022). Global energy demand fell by 3.8% in the first quarter of 2020, compared with the previous year (IEA, 2020), and industrial coal demand dropped by 8% due to a decrease in electricity needs (Broom, 2020), even though there was an increase in residential electricity demand (Hinson, 2020). For China, as shown in Fig. 1, the total CO2 emission decreased by 5.5%, 1.9%, and 0.3% in the first three quarters of 2020, and then it increased by 1.3% in the last quarter. It can be seen that, COVID-19 has negative effects on economic output, however, it brings about positive effect on CO2 emissions reduction.

As a responsible major developing country, China has always attached great importance to the issue of climate change and taken addressing climate change as a major national strategy for economic and social development. In September 2020, Chinese President Xi Jinping announced in his speech at the general debate of the 75th Session of the United Nations General Assembly that China would increase its nationally determined contribution and adopt more effective policies and measures to peak carbon dioxide (CO2) emissions by 2030 and achieve
carbon neutrality by 2060, and will make greater efforts and contributions to achieving the targets set in the Paris Agreement on climate change (Xinhua News Agency, 2021a).

China’s COVID-19 vaccine has been successfully developed, produced and inoculated, and the countdown to the end of COVID-19 may be gradually approaching. However, this does not mean that research on the current situation of China’s economy during the COVID-19 pandemic has lost its value. There may be several waves of the pandemic in the future, which is predicted potentially to last until 2024, and thus prolonged or intermittent social distancing are likely to be continued at least until 2022 (Kissler et al., 2020). China’s supply chains have been seriously affected even after the pandemic, with profound impacts on CO₂ emissions. On the contrary, COVID-19 is the largest public health security event since the outbreak of SARS in 2003. Lessons from history show that, there are often significant macroeconomic after-effects of pandemics (Jorda et al., 2020). Accelerated economic development over recent decades has linked producers and consumers across China, which is still connected via a highly interdependent production system. The economic impacts of COVID-19 and lockdown policies will be amplified via the ripple effects through supply chains most likely continuing throughout the coming years (Davis et al., 2022). Thus, it is of great significance to study the positive effect on CO₂ emissions reduction by COVID-19 so that to control the CO₂ emissions in the economic recovering phase.

Compared with previous studies on socioeconomic impacts of disasters, there are something difference from other studies as follows:

Firstly, even though COVID-19 brings about lots of negative effects to the whole world, for example the loss of health and life, the decrease of economy, CO₂ emissions decrease at the same time. Previous studies mainly focus on negative effects of COVID-19 on economy, however the positive effects on CO₂ emission reduction are rarely studied. This study expands the research dimension, not only examines negative effects of COVID-19 on economy, but also the positive effects of COVID-19 on carbon emission reductions. Therefore, this study is of unique guiding significance not only for the construction of economic recovery in the latter half of the COVID-19 epidemic, but also for the CO₂ emissions mitigation in the meanwhile, which can give suggestions for governments how turn the crisis into an engine for climate action.

Secondly, in order to reflect the relative impacts of COVID-19 on the economic system and related CO₂ emissions relative to the absence of the pandemic, a proper method is needed. However, existed methods used to reflect the impacts of external shocks have some problems such as the improper setting of reality scenes which cannot better reflect the economic loss and CO₂ emission reduction. In this study, a new model named “weighted hypothetical extraction model” is put forward in order to solve the shortcomings of traditional methods, which can not only measure the economic loss but also the CO₂ emission reduction affected by COVID-19, which is unique compared with the previous research models.

Thirdly, different from most studies which only concern about the direct economy loss or CO₂ emissions of an industry or province, this study accounts for not only direct economic loss and CO₂ emissions reduction of an industry or province under COVID-19, but also captures indirect industrial/regional impacts of COVID-19. By applying the new model, the impacts of a provincial sector on its upward and backward sectors and provinces can be measured through the ripple effects of the supply chain. Ultimately, the direct and indirect economic and CO₂ emission effects of COVID-19 on China can be measured.

Fourthly, in order to choose key sectors conducive to economic recovery in the post-epidemic era in a green way, this article combined both the economic and CO₂ emissions effects together from forward and backward perspectives respectively. The key sectors are selected considering two periods of the epidemic serious period and economy recovery period. On the one hand, key reduction sectors which can reduce CO₂ emissions but not affect the development of economy are selected; on the other hand, the encouraged sectors which can increase economy with CO₂ emissions are also identified.

In addition, since the variations of COVID-19 and its effects on economy or CO₂ emissions are different in each month and in each sector, it is necessary to study these effects month by month at the industrial level. So, the monthly economy or CO₂ emissions data is necessary. As for previous studies appeared to study the variation of CO₂ emissions are mostly based on annual data to evaluate, this paper uses monthly data to break through the problems of insufficient research accuracy caused by previous annual data, and can observe the impact of external factors more dynamically. The data used in this paper are monthly data of each industry in all provinces, including the provincial sectoral added values and CO₂ emissions data, which can better reflect these dynamic effects of COVID-19.

2. Literature review

Recent studies estimate CO₂ emission reduction during the COVID-19 pandemic using statistical activity data as a bottom-up method (Arshad, 2020), or using satellite-observed retrieval data as a top-down method (Zheng, B. et al., 2020). As for bottom-up method, some studies...
(Le Quéré et al., 2020; Liu et al., 2020) compiled energy consumption data for residential, industrial, and mobile activities, and estimated the monthly CO₂ emissions from each source. However, the lack of daily energy data renders the statistical data subject to inaccuracies in fuel consumption and composition (Konovalov et al., 2016). As for Top-down method, the daily changes in CO₂ emissions were estimated to agree with the changes in the observed NO₂ column concentration, because NO₂ is committed with CO₂ from the combustion of fossil fuel and other fuels.

It can be seen that indicators used to measure CO₂ emission are usually based on production perspective (Sim et al., 2022), while some conventional indicators are used to assess the performance of the national economy such as domestic production, gross national income, and economic growth rate. These indicators can well measure the amount of direct economic loss and CO₂ emission reduction from COVID-19, but the indirect economy loss and CO₂ emission reduction under the COVID-19 will trigger the economy of the total chain reaction, which will continuously intensify, amplify and expand their influence through circulation and causality accumulation. And it eventually produces losses multiplier effect, and affects the stability of the national economic structure and CO₂ emission reduction. Different from simple and intuitive economic and CO₂ emission indicators, industrial linkage effect refers to the direct and indirect economy and its related CO₂ emission effects of all kinds of related relations on other industries induced by the changes of various elements of an industry.

Some well-known models like CGE model, Input-output (IO) model, and hypothesis extraction method (HEM) model based on IO model are applied to assess economic impacts of COVID-19 (Mandez and Veetil, 2020). These models used to assess disaster impact due to their ability to reflect interdependencies of economic sectors. CGE models are non-linear in common practice, can respond to price changes, can accommodate input and import substitutions, and can explicitly handle supply constraints. As a simulation model, the CGE model can integrate disaster-specific features as an endogenous function (Okuyama and Santos, 2014). However, the CGE model potentially provides lower impact estimates than IO models, partly because not all causations in CGE models are unidirectional, and functional relationships often offset each other (Koks et al., 2016). As the IO model, it is more suitable to capture the impact of sudden shocks on the economy. However, due to a lack of the adaptive behaviors of economic agents in a disaster aftermath, IO model may overestimate the impacts of a disaster (Shan et al., 2021). For traditional HEM, there are some problems such as improper use of assumptions, over-reliance on industrial intermediate inputs and failure to accurately reflect the impact of external shocks on inter-industry association (Ali et al., 2019; Dietzenbacher et al., 2019). It is difficult for a complex economy to see the "disappearance" of an entire industry even under the impact of a catastrophe such as COVID-19. Therefore, it is necessary to propose a new input-output model to solve the above problems.

In order to complement these studies, the Weighted Multi-regional Hypothetical Extraction Method (WMHEM) based on IO model is put forward in our study. There are some main distinctions between the method in our study with existed CGE, IO and traditional HEM model. On the one hand, the existed models mainly measure the influence on economic development and carbon emissions of other sectors induced by the final demand of a sector; but for the method of this study, it measures the losses of economy and carbon emissions of other sectors and regions under the influence of COVID-19 induced by the loss of the final demand of a sector, which measures the loss values. On the other hand, the existed models measure the overall changes of economy and carbon emissions of a sector during a period of time; but the method of this study can differentiate the economic natural changes and the changes caused by the outbreak of COVID-19, which can measure the direct and indirect economic loss and CO₂ emission reduction induced by a sector only due to COVID-19 more accurately. Therefore, the WMHEM in our study is more advantageous in studying the impact of external shocks especially COVID-19 on the economy, and related CO₂ emission reduction.

3. Material and methods

3.1. Environmentally extended multi-regional input-output analysis

Input-output analysis was first proposed by Leontief in 1936 (W., 1936) and is widely used to evaluate resource and environmental issues (Feng et al., 2019g; Zhang et al., 2021). The MRIO model is a top-down method and has advantages in assessing the regional disparities and inter-regional trade of goods and services (Feng et al., 2019b; Jin et al., 2019). In the framework of input-output analysis, there is an equilibrium between the output and final demand calculations in the MRIO model. It can be expressed as follows (Leontief, 2011):

\[ X = AX + Y \]  

(1)

The total output X is linked to the final demand Y via

\[ X = (I - A)^{-1} Y \]  

(2)

Where (1) vector X indicates the total output of an economy; (2) vector Y is the final consumption of specific amounts of products produced in each sector; (3) matrix \((I - A)^{-1}\) is the Leontief inverse matrix, which indicates the total amount of direct and indirect inputs to meet one unit of final demand; (4) I is an identify matrix; (5) A is a direct input coefficient matrix encompassing the relationships among sectors. \(a_{ij}\) is an element of A and reflects the amount of input from sector \(i\) in province \(r\) directly required to produce one unit output from sector \(j\) in province \(s\) as follows:

\[ A = \left\{ a_{ij} \right\} = \left\{ \frac{e_{ij}}{x_{j}^r} \right\} \quad (r, s = 1, 2, ..., m; i, j = 1, 2, ..., n) \]  

(3)

Where the element \(e_{ij}^r\) is intermediate input from sector \(i\) of province \(r\) to sector \(j\) of province \(s\) \((r, s = 1, 2, ..., m; i, j = 1, 2, ..., n)\) and \(x_{j}^r\) is the total output of sector \(j\) in province \(s\).

The embodied CO₂ emissions \(E\) in an economy represent the CO₂ emissions measured by a consumption-based method and required to meet the final demand. It can be calculated as follows:

\[ E = d \times (I - A)^{-1} Y \]  

(4)

Where \(d\) is a \(1 \times n\) column vector of the CO₂ emission intensity of each sector in all provinces, which can be expressed as follows:

\[ d = E/X \]  

(5)

3.2. Traditional Hypothetical Extraction Method (HEM)

HEM assumes to extract an industry from an economic system and evaluate the impact of the industry on the overall economy and its linkage effect with other industries according to the difference of the total social output before and after extraction (Dietzenbacher et al., 2019; Yuan et al., 2017). It is used to measure the ripple effect and industrial strategic position of industrial association in agriculture (Yang et al., 2014), industry (Nal, 2020), construction industry (Song et al., 2006) and tertiary industry (Byeon et al., 2017; Xia et al., 2019). For traditional HEM, it divides all regions and industries of the economic system into two parts based on the multi-regional input-output model. \(D_i^p\) represents an industry block \(i\) \((i = 1, 2, ..., n)\) composed by simple or multiple industries of the studied region \(p\) \((p = 1, 2, ..., m)\), \(D^p\) represents the industry block \(j\) formed by all other industries in region \(P\) and other regions, the industry matrix \(D\) can be expressed as:
The total output of $X$ can be decomposed into:

$$X^p = A_{0}^p \times X^p + Y^p = \begin{bmatrix} L_{00}^p & L_{01}^p & L_{02}^p & \cdots & L_{0n}^p \\ L_{10}^p & L_{11}^p & L_{12}^p & \cdots & L_{1n}^p \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ L_{n0}^p & L_{n1}^p & L_{n2}^p & \cdots & L_{nn}^p \end{bmatrix} \begin{bmatrix} Y^p_1 \\ Y^p_2 \\ \vdots \\ Y^p_n \end{bmatrix}$$

(7)

Among them,

$$(I - A)^{-1} = \begin{bmatrix} L_{00}^p & L_{01}^p & L_{02}^p & \cdots & L_{0n}^p \\ L_{10}^p & L_{11}^p & L_{12}^p & \cdots & L_{1n}^p \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ L_{n0}^p & L_{n1}^p & L_{n2}^p & \cdots & L_{nn}^p \end{bmatrix}$$

(8)

After extracting the industry block, assuming that the industry block $D^f$ no longer trades with other industries, the extracted economic system composition $X^p$ can be decomposed into:

$$X_i^p = \begin{bmatrix} A_{0i}^p & 0 & \cdots & 0 \\ 0 & A_{i1}^p & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & A_{in}^p \end{bmatrix} \begin{bmatrix} X_i^p \\ X_{i1}^p \\ \vdots \\ X_{in}^p \end{bmatrix} + \begin{bmatrix} Y^p_i \\ Y^p_{i1} \\ \vdots \\ Y^p_{in} \end{bmatrix}$$

$$= \begin{bmatrix} (I - A^p_{ii})^{-1} & 0 & \cdots & 0 \\ 0 & (I - A^p_{i1})^{-1} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & (I - A^p_{in})^{-1} \end{bmatrix} \begin{bmatrix} Y^p_i \\ Y^p_{i1} \\ \vdots \\ Y^p_{in} \end{bmatrix}$$

(9)

The influence of extracted industries on total output is as follows:

$$X - X_i^p = \begin{bmatrix} X_j^p - X_{ji}^p \\ X_{j1}^p - X_{j1i}^p \\ \vdots \\ X_{jn}^p - X_{jn1}^p \end{bmatrix} + \begin{bmatrix} L_{j0}^p & L_{j1}^p & L_{j2}^p & \cdots & L_{jn}^p \\ L_{j10}^p & L_{j11}^p & L_{j12}^p & \cdots & L_{j1n}^p \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ L_{jn0}^p & L_{jn1}^p & L_{jn2}^p & \cdots & L_{jnn}^p \end{bmatrix} \begin{bmatrix} Y^p_j \\ Y^p_{j1} \\ \vdots \\ Y^p_{jn} \end{bmatrix}$$

$$= \begin{bmatrix} L_{j0}^p & L_{j1}^p & L_{j2}^p & \cdots & L_{jn}^p \\ L_{j10}^p & L_{j11}^p & L_{j12}^p & \cdots & L_{j1n}^p \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ L_{jn0}^p & L_{jn1}^p & L_{jn2}^p & \cdots & L_{jnn}^p \end{bmatrix} \begin{bmatrix} Y^p_j \\ Y^p_{j1} \\ \vdots \\ Y^p_{jn} \end{bmatrix}$$

(10)

3.3. Weighted Multi-regional Hypothetical Extraction Method (WMHEM)

Recent researchers modified traditional HEM by using vertical Integrated Processes and established GHEM, which is widely used in the analysis of water resource utilization (Deng et al., 2018; He et al., 2020), energy consumption (Dietzenbacher et al., 2019) and pollution emission (Sajid et al., 2019; Zhang, L. et al., 2020) of various industries in the economic system. However, GHEM does not solve the problem of improper use of analytical assumptions in the process of assumption elimination, which leads to various deviations in the industrial linkage measurement results and economic interpretation.

To compensate for the limitations of traditional HEM, a new method, Weighted Multi-regional Hypothetical Extraction Method (WMHEM), was put forward in our study to solve these problems. We constructs an indicator matrix $w$ that uses weights to measure the actual changes in sectors referring to the idea of using weights for sector simulation (Mao et al., 2018). It mainly uses the difference between the year-on-year growth rate of the sector’s actual economic added value and that of the expected economic added value to measure the damage of a sector under external shock. It lets the sector fuse in a corresponding proportion according to the actual situation, so as to understand the impact of external shocks on the economic system and solve the problem that traditional HEM is out of reality and cannot reflect external shocks.

The matrix $w$ reflects the degree of economic loss caused by the external shock to the sector, and the form is as follows:

$$w = [ w_1 \cdots w_i \cdots w_n ]$$

(11)

Where

$$w_i = \sqrt{\frac{N_{0i}}{N_{0i-1}}} \times 100\% - 100\% - \frac{IV_i - IV_0}{IV_0} \times 100\%$$

(12)

Among them, $a$ and $b$ are the termination and starting observation time of the expected economic value added respectively, and $N_0$ and $N_{0-1}$ are the economic value added in the corresponding years. Where, $a$ and $b$ jointly determine the observed time length of the expectancy value of the change rate of economic added value of each industry. If this time length is too long, the explosive growth of emerging industries may be ignored; while if it is too short, the actual growth capacity of this industry may be misjudged due to the special circumstances of a certain year. Therefore, the observation period is set as three years in the study to better represent the expected growth of economic added value of a certain industry. In this study, $a$ and $b$ correspond to three years ago of the study period, namely $a$ is from December 2019 to May 2020, and $b$ is from December 2016 to May 2017. $IV_i$ is the economic added value of the sector in the current period (or a surrogate value that can reflect the actual production level of the industry), and $IV_0$ is the economic added value of the sector in the same period last year (or a surrogate value that can reflect the actual production level of the industry). Economic value added refers to the difference between the total monetary value of the production or service produced by an enterprise or a sector within a certain period of time and the total monetary value of its consumption. The sum of the economic added value of each sector in the national economy is the gross domestic product. $w_i$ is the difference between the expected and the actual year-on-year change rates which represents the extent of the sector’s loss after the shock. When $w_i > 0$, the normal production activities of the sector are negatively affected. When $w_i < 0$, the normal production activities of the sector are positively affected. Through the matrix $w$, the direct loss of each sector in a certain period can be grasped. Based on this, the impact of external shocks on the structure of various sectors can be studied, and then the impact of external shocks on the overall economic system can be understood.

3.3.1. The “economic negative effect” and “CO$_2$ emission positive effect”

Based on the WMHEM, the effects on economy and CO$_2$ emissions during COVID-19 are calculated.

The “economic negative effect” means the economic losses of a region or sector induced by COVID-19. Because the economic losses are not what people desired, we regard economic losses of a region or sector induced by COVID-19 as “economic negative effect” of COVID-19. If the “economic negative effect” is greater than 0, it means that the region or sector has been negatively affected by COVID-19 and has got the economic losses. If the “economic negative effect” is less than 0, it means that the region or sector has not been affected by COVID-19 on the economy and has got the economic growth.

The “CO$_2$ emission positive effect” means that the amount of CO$_2$ emissions reduction that a region or sector has been affected by the impact of COVID-19. Because the CO$_2$ emissions reduction is what people desired, so we regard CO$_2$ emissions reduction of a region or sector induced by COVID-19 as CO$_2$ emission positive effects of COVID-19. If the “CO$_2$ emission positive effect” is greater than 0, it means that the region or sector has been positively affected by COVID-19, resulting in a reduction in CO$_2$ emissions. If the “CO$_2$ emission positive effect” is less than 0, it means that the region or sector has not been affected by COVID-19 on CO$_2$ emissions, and has got increase in CO$_2$ emissions.

As shown in Fig. 2, this is a simple supply chain constituted by three sectors: A represents the upstream sector which is for the acquisition of raw materials; B is an intermediate transmission sector which produces the intermediate goods; and C is a downstream sector which produce the final products. The supply chain path shows the production process starting from sector A, then pass through the intermediate sector B, and to the end sector C, which make products for final uses such as household, government, and capital formation. Based on the simple supply chain: some concepts used in this study can be defined as follows:

At first, from the forward linkage perspective: (a) Forward economic linkage: it reflects the production increase in all sectors pushed by a unitary increase of added value of sector A; (b) Forward CO$_2$ emission linkage: when the “total output” is substitute to “total CO$_2$ emissions”, the forward economic linkage changes to be forward CO$_2$ emission
Fig. 2. Conceptual graph of economic and CO2 emission linkages, and economic and CO2 emissions effects of COVID-19. Forward linkage is in purple color, and backward linkage is in blue color.

linkage, which reflects the CO2 emissions of all sectors caused by a unitary increase in primary input of sector A; ② Forward negative economic effect: it is put forward in this study which evaluates the economic forward linkage loss caused by the lockdown policies implemented during COVID-19; ③ Forward positive CO2 emission effect: it is also a new concept created by this study to assess the volume of forward CO2 emission linkage cut down due to the reduction in activities during lockdown period.

While from the backward linkage perspective: ⑤ Backward economic linkage: it reflects the total economic growth in all sectors by one unit of final demand of sector C; ⑥ Backward CO2 emission linkage: it reflects the CO2 emissions of all sectors caused by a unitary increase in final demand of sector C; ⑦ Backward negative economic effect: just as ③, it reveals the economic backward linkage loss caused by the lockdown policies implemented during COVID-19; ⑧ Backward positive CO2 emission effect: it is exactly as ③ to assess the volume of backward CO2 emission linkage reduced by lessened activities during lockdown period.

3.3.2. The “economic negative effect”

(1) The forward “economic negative effect”

It is assumed that the input of $D_i^p$ to other industries decreases according to $w_i$ due to external factors during the COVID-19 outbreak, but the input-output within this industry block and the output from other industry blocks are not affected, then the output of this economic system under the COVID-19 outbreak is:

$$
\begin{bmatrix}
X_i^{p,\text{Forward}} \\
X_i^{w,\text{Forward}}
\end{bmatrix} = \begin{bmatrix} A_{ij}^{p} & (1-w_i^p)A_{ij}^{wp} \end{bmatrix} \begin{bmatrix}
X_j^{p} \\
X_j^{w}
\end{bmatrix} + \begin{bmatrix} Y_j^{p} \\
Y_j^{w}
\end{bmatrix}
$$

(13)

The amount of forward economic linkage loss can be expressed as:

$$X_i^{\text{Forward}} = X_i - X_i^{p,\text{Forward}} = \begin{bmatrix}
X_i^{p} - X_i^{p,\text{Forward}} \\
X_i^{w}
\end{bmatrix} = \begin{bmatrix}
L_i^{p} - (1-A_{ij}^{p})^{-1} & L_i^{wp} - (1-A_{ij}^{wp})^{-1} \\
L_i^{w} - (1-A_{ij}^{w})^{-1} & L_i^{wp} - (1-A_{ij}^{wp})^{-1}
\end{bmatrix} \begin{bmatrix} Y_j^{p} \\
Y_j^{w}
\end{bmatrix}
$$

(14)

(2) The backward “economic negative effect”

It is assumed that the output of $D_i^p$ from other industries decreases according to $w_i$ due to external factors during COVID-19, but the input-output within this industry block and the output to other industry blocks are not affected, then the output of this economic system under COVID-19 is:

$$
\begin{bmatrix}
X_i^{p,\text{Backward}} \\
X_i^{w,\text{Backward}}
\end{bmatrix} = \begin{bmatrix} A_{ij}^{p} & (1-w_i^p)A_{ij}^{wp} \end{bmatrix} \begin{bmatrix}
X_j^{p} \\
X_j^{w}
\end{bmatrix} + \begin{bmatrix} Y_j^{p} \\
Y_j^{w}
\end{bmatrix}
$$

(15)

The amount of backward linkage loss can be expressed as:

$$X_i^{\text{Backward}} = X_i - X_i^{p,\text{Backward}} = \begin{bmatrix}
X_i^{p} - X_i^{p,\text{Backward}} \\
X_i^{w}
\end{bmatrix} = \begin{bmatrix}
L_i^{p} - (1-A_{ij}^{p})^{-1} & L_i^{wp} - (1-A_{ij}^{wp})^{-1} \\
L_i^{w} - (1-A_{ij}^{w})^{-1} & L_i^{wp} - (1-A_{ij}^{wp})^{-1}
\end{bmatrix} \begin{bmatrix} Y_j^{p} \\
Y_j^{w}
\end{bmatrix}
$$

(16)

3.3.3. The “CO2 emission positive effect”

(1) The forward “CO2 emission positive effect”

The CO2 emission data $c_i^p$ of $D_i^p$ is introduced and the carbon emission coefficient $mc_i^p$ of $D_i^p$ is obtained as follows:

$$mc_i^p = \frac{c_i^p}{X_i}
$$

(19)

The carbon emission coefficient means the direct carbon dioxide emissions produced by per unit of economic output of a sector. By combining with the carbon emission coefficient $mc_i^p$ and the forward associated loss $X_i^{\text{Forward}}$, the forward carbon emission linkage loss $c_i^{\text{Forward}}$ can be obtained:

$$c_{ij}^{\text{Forward}} = \begin{bmatrix}
mc_i^p & 0 \\
mc_j^p
\end{bmatrix} \begin{bmatrix}
L_i^{p} - (1-A_{ij}^{p})^{-1} & L_i^{wp} - (1-A_{ij}^{wp})^{-1} \\
L_j^{p} - (1-A_{ij}^{w})^{-1} & L_j^{wp} - (1-A_{ij}^{wp})^{-1}
\end{bmatrix} \begin{bmatrix} Y_j^{p} \\
Y_j^{w}
\end{bmatrix}
$$

(20)
Forward CO₂ emission linkage loss intensity coefficient $\gamma_{i}^{\text{forward}}$ is as follows:

$$\gamma_{i}^{\text{forward}} = \sum \sum \left[ \frac{C_{i}^{(\text{Forward})}}{C_{i}^{(\text{Forward})}} \right] = \sum \sum \left[ \frac{m_{c}^{p}}{m_{c}^{p}} \right] \begin{bmatrix} L_{i}^{p} & (I - A_{i}^{p})^{-1} & L_{i}^{p} - (I - A_{i}^{p})^{-1} \end{bmatrix} \begin{bmatrix} \gamma_{i}^{p} \gamma_{i}^{p} \gamma_{i}^{p} \end{bmatrix}$$

(2) The backward “CO₂ emission positive effect”

Combined with the CO₂ emission coefficient $m_{c}^{p}$ and the forward associated loss $X_{i}^{(\text{Backward})}$, the forward carbon emission linkage loss $C_{i}^{(\text{Backward})}$ can be obtained:

$$C_{i}^{(\text{Backward})} = \begin{bmatrix} m_{c}^{p} & 0 & \gamma_{i}^{p} \\ 0 & m_{c}^{p} & \gamma_{i}^{p} \end{bmatrix} \begin{bmatrix} L_{i}^{p} & (I - A_{i}^{p})^{-1} & L_{i}^{p} - (I - A_{i}^{p})^{-1} \end{bmatrix} \begin{bmatrix} \gamma_{i}^{p} \gamma_{i}^{p} \gamma_{i}^{p} \end{bmatrix}$$

On the one hand, because of the limitation of monthly CO₂ emissions data for each industry in all provinces; on the other hand, the most serious and most representative period of the COVID-19 is from December 2019 to May 2020. Thus, this period is regarded to be the research period of this article. Further, it is divided into two periods: the epidemic serious period (December 2019—March 2020) and economy recovery period (April 2020—May 2020).

3.4.1. Range of study

In December 2019, COVID-19 was reported in Wuhan, China, and soon outbreak all over the world rapidly (Pcn et al., 2020; Remuzzi and Remuzzi, 2020). After the outbreak of COVID-19, the Wuhan government locked the city down on January 23, 2020, to prevent further spreading, and other cities across the country were forced to be under lockdown in quick succession. The government advocated citizens to stay at home to lessen infections and deaths. Under this circumstance, most of the production activities were halted and outdoor activities were dramatically decreased. The resumption of production has been taking place since March 2020. At the end of April, most of the major industries restarted their production, and people’s lives gradually returned to normalcy as shown in Fig. 1.

### Table 1

| Statistics description of the vector $\mathbf{w}$ on industry level. |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|                | Dec. 2019       | Jan.–Feb. 2020  | Mar. 2020       | Thu. 2020       | May. 2020       |
| Mean            | -0.0160         | 0.0990          | 0.0997          | 0.0268          | 0.0268          |
| Median          | -0.0202         | 0.0948          | 0.0830          | 0.0164          | 0.0107          |
| Max             | 1.0146          | 0.7935          | 0.8072          | 0.6764          | 0.6636          |
| Min             | -0.9618         | -0.6376         | -0.6376         | -0.3914         | -0.3593         |
| Variance        | 0.0135          | 0.0383          | 0.0350          | 0.0167          | 0.0165          |
| Standard Deviation | 0.1161         | 0.1956          | 0.1870          | 0.1293          | 0.1284          |

The data needed in this article concludes three aspects as follows:

(1) Multi-regional input-output tables

In our research, Chinese MRIO table in 2017 (Zheng, H. et al., 2020) is adopted. The MRIO table depicts provincial trade in China and includes data for 30 provincial administrative regions (not including Tibet, Hong Kong, Macao and Taiwan). In addition, the table is noncompetitive tables, and it is assumed that all of the imports are noncompetitive. The table excludes all of the imports from provincial trade in China and can avoid the overestimation issues commonly encountered in empirical...
studies. The 30 provincial administrative regions studied are listed in Appendix Table A1.

(2) CO₂ emissions data

The direct carbon dioxide emission data for 13 industries in 30 provinces (a total of 390 provincial sectors) from December 2019 to May 2020 are from the data published by Wang et al. (2020) (https://doi.org/10.1016/j.xinn.2020.100062). Bottom-up and top-down methods are both used here to estimate the CO₂ emission reduction during the COVID-19 pandemic.

(3) Economy data

The monthly economic added value of S1 of each province is calculated by the quarterly agricultural added value published by the National Bureau of Statistics. S2–S13 are calculated by the comprehensive calculation of monthly industrial added value of each province published by National Bureau of Statistics.

(4) The value of vector w

The values of vector w for all industries have been attached in the Appendix. Table 1 shows the statistical indicators of vector w. It can be found that the average value of vector w was less than 0 in December 2019, indicating that the majority of industries were not affected seriously in December 2019 under the pandemic. The average value of vector w peaked in March 2020, and then decreased significantly, indicating that the economic linkage loss level of industries rose sharply from January 2020 and reached its peak in March, and gradually decreased over time. As for the variance and standard deviation, they were higher during January–February in 2020 than other periods, indicating that there was a large difference in economic linkage losses among different industries of different provinces in the early stage of the COVID-19 epidemic. This is because that, at the beginning of the COVID-19 outbreak, the severity of the epidemic was different in different regions (such as the lockdown in Hubei).

4. Results and discussion

4.1. Industrial economic and carbon emissions effects

4.1.1. The “economic negative effect”

At industry level, “economic negative effect” is analyzed in Fig. 3. Based on the forward linkage, Other Industries (S10) (293.62 billion RMB), Wholesale, Retail Trade and Catering Services (S11) (377.28 billion RMB), Transport, storage, and postal services (S12) (339.82 billion RMB), Other Service Sectors (S13) (314.50 billion RMB) had the most “economic negative effect” in January to February in 2020. The growth rates of economic value added in these sectors have dropped significantly compared with the past three years (National Bureau of Statistics of China), so their “economic negative effect” were relatively high. Their impacts of economic losses on downstream sectors were mainly concentrated in Construction (S9), Other Industries (S10), and Other Service Industries (S13). From March in 2020, their “economic negative effect” began to decreased. This is due to the fact that in March 2020, the central and provincial governments of China successively issued a series of policies to strengthen fiscal and taxation support for small, medium and micro enterprises to help enterprises overcome the impact of COVID-19, mainly including Other Industries (S10), Wholesale, Retail Trade and Catering Services (S11), and Other Service Sectors (S13) (Department of Social Security of the Ministry of Finance of the People’s Republic of China, 2020). In addition, the Ministry of Transport also issued preferential fiscal and tax policies to promote the implementation of Transport, storage, and postal services (S12) (Ministry of Transport of the people’s Republic of China, 2020), which has promoted the economic recovery of Transport, storage, and postal services (S12). Therefore, these policies have provided assistance for the economic recovery of these industries under COVID-19, and their economic linkage losses have been gradually reduced.

While the value of Agriculture, Forestry, Animal Husbandry and Fishery (S1) (–173.37 billion RMB) was the least and negative in January to February in 2020, but negative absolute value decreased in April and May. This is because that, from the end of January to late March, the Chinese government issued 16 urgent notices to ensure an ample supply of food, effective logistics for delivering agricultural inputs and support agricultural production. Since the government took these measures, the problems in agricultural production have been effectively alleviated. (Pu and Zhong, 2020). It means that even though the “economic negative effect” of other sectors increased in January to February 2020, the added value of the whole industrial chain pushed by the input of Agriculture, Forestry, Animal Husbandry and Fishery (S1) still grew.

Based on the backward linkage, Construction (S9) (1391.45 billion RMB) and Other Industries (S10) (1097.29 billion RMB) had the most
in January to February 2020 and then decreased later. Because the growth rate of the economic added value of them has dropped significantly from January to February compared with the past three years, so the “economic negative effect” of them was relatively high. The “economic negative effect” of Construction (S9) on the national economy was the highest (1391.45 billion RMB), but the direct economic loss was 388.28 billion RMB. The “economic negative effect” of Other Industries (S10) in February was 1097.29 billion RMB (the direct economic loss was 354.40 billion RMB). This is because from January to February 2019, many governments requested Construction (S9) to suspend work resumption, and even some areas did not officially resume work until mid-March, such as Shandong (Shandong Provincial Department of Housing and Urban-Rural Development, 2020) and Jiangxi (Xinhua News Agency, 2020a). Other Industries (S10) also basically resumed to work in February–March, such as Heilongjiang Province People’s Government (2020) and Hubei (Xinhua News Agency, 2020b). This affected the production of Construction (S9) and Other Industries (S10), which in turn affected their demand for upstream sectors, so the economic linkages of these two sectors pulling upstream sectors were severely damaged.

Just like its forward economic linkage, due to the targeted agricultural policy support, the value of Agriculture, Forestry, Animal Husbandry and Fishery (S1) (−40.67 billion RMB) was the least and negative too. But its negative absolute value was less than its forward linkage, meaning that the economic output of the whole industrial chain induced by the demand of Agriculture, Forestry, Animal Husbandry and Fishery (S1) also increased. The economic growth caused by the increased demand for S1 was mainly concentrated in its downstream sector Other Industries (S10).

4.1.2. The “CO₂ emission positive effect”

“CO₂ emission positive effect” are displayed in Fig. 4. As for forward “CO₂ emission positive effect”, Production and distribution of electric power and heat power (S8) (27.77 million tons) got the most in December 2019, and it keep being the most until May 2020 (28.21 million tons). This is due to the fact that China’s electricity demand in the first quarter fell by more than 3% year-on-year, so the Production and distribution of electric power and heat power (S8) brought about significantly lower carbon emissions from the supply of products to downstream sectors (International Energy Agency, 2020). For Processing of petroleum, coking, processing of nuclear fuel (S4), its forward “CO₂ emission positive effect” was negative during December 2019 (−8.42 million tons) to February 2020 (−3.21 million tons), then it increased to be the most in March (46.26 million tons), and then decreased in April (7.08 million tons), and to be negative value (−17.27 million tons) again in May. It means that, it promoted CO₂ emissions at the beginning of the COVID-19; due to the COVID-19, the promoted CO₂ emissions decreased a lot but it recovered easily and had large CO₂ emission potential. This is because some derivatives of the Processing of Petroleum, Coking, and Processing of Unclear Fuel (S4) are important raw materials for the manufacture of medical masks. The surge in demand for the mask in a short term from January to February led to a
surge in the market demand for PP (especially polypropylene high-melting fiber) in S4. Therefore, it drove the increase of national CO\textsubscript{2} emissions from January to February, and had a negative value in “CO\textsubscript{2} emission positive effect”. Then, like most other sectors, the growth rate of economic value added of S4 decreased greatly in March, resulting in the maximum “CO\textsubscript{2} emission positive effect” (46.22 million tons).

As for the backward linkage, Construction (S9), Other Industries (S10), Transport, storage, and postal services (S12) and Other Service Sectors (S13) had the most “CO\textsubscript{2} emission positive effect” in December 2019 and then decreased later, that was similar to the situation based on forward linkage. Because Construction (S9), Other Industries (S10), Transport, storage, and postal services (S12) had higher CO\textsubscript{2} emission intensities, and their backward economic linkages were greatly damaged. Therefore, the losses of CO\textsubscript{2} emission linkage were also large, and their backward “CO\textsubscript{2} emission positive effect” were relatively significant. Similarly, for Processing of petroleum, coking, processing of nuclear fuel (S4), its backward “CO\textsubscript{2} emission positive effect” was negative in December 2019 (−1.83 million tons), and then changed to be positive in January to February 2020 (2.24 million tons), then it increased to be the most in March (10.20 million tons), and then decreased in April (1.37 million tons), and to be negative value again in May (−2.66 million tons). However, the value was less than that based on forward linkage. It means that, although affected by the COVID-19, the CO\textsubscript{2} emissions increase of the whole industrial chain driven by Processing of petroleum, coking, processing of nuclear fuel (S4) can recover quickly.

4.2. Provincial economic and carbon emissions effects

4.2.1. The “economic negative effect”

The “economic negative effect” in each province is displayed in Fig. 5. When seen from forward “economic negative effect”, there was some difference. It began to occur in all provinces from January to February 2020, with Hubei (265.47 billion RMB) being the largest, followed by Shandong (110.03 billion RMB) and Guangdong (141.04 billion RMB). In Hubei, due to the closure of the province in the early stage of the epidemic, most sectors were unable to operate normally, and the growth rate of the economic added value of each sector has dropped significantly compared to last month. In May, the CO\textsubscript{2} emissions positive effect of Hubei and Liaoning (12.37 million tons) increased a lot, and Hubei (54.21 million tons) got the most “CO\textsubscript{2} emission positive effect” among all of the provinces. This is because Petroleum coke (S4) and electric heating water (S8) of these provinces, which have higher carbon emissions per unit of output, had the highest positive effect on carbon emissions nationwide. In March, most of the provinces were received “CO\textsubscript{2} emission positive effect”. Hubei (32.82 million tons) also had the largest “CO\textsubscript{2} emission positive effect”, but the value decreased a lot compared to last month. In May, the “CO\textsubscript{2} emission positive effect” on some provinces changed to be negative, such as Jilin (−2.67 million tons), Jiangsu (−2.16 million tons) and Gansu (−2.12 million tons), which means the CO\textsubscript{2} emissions promoted by these provinces began to increase. As the growth rate of economic added value of petroleum coke (S4) in the three provinces were significantly higher than that of the past years, which lead to carbon emissions increase.

4.2.2. The “CO\textsubscript{2} emission positive effect”

“CO\textsubscript{2} emission positive effect” in each province are displayed in Fig. 6. Forward “CO\textsubscript{2} emission positive effect” on Xinjiang (5.07 million tons) and Inner Mongolia (5.02 million tons) were the most in December 2019. While in January to February 2020, forward “CO\textsubscript{2} emission positive effect” on Hubei and Liaoning (12.37 million tons) increased a lot, and Hubei (54.21 million tons) got the most “CO\textsubscript{2} emission positive effect” among all of the provinces. This is because Petroleum coke (S4) and electric heating water (S8) of these provinces, which have higher carbon emissions per unit of output, had the highest positive effect on carbon emissions nationwide. In March, most of the provinces were received “CO\textsubscript{2} emission positive effect”. Hubei (32.82 million tons) also had the largest “CO\textsubscript{2} emission positive effect”, but the value decreased a lot compared to last month. In May, the “CO\textsubscript{2} emission positive effect” on some provinces changed to be negative, such as Jilin (−2.67 million tons), Jiangsu (−2.16 million tons) and Gansu (−2.12 million tons), which means the CO\textsubscript{2} emissions promoted by these provinces began to increase. As the growth rate of economic added value of petroleum coke (S4) in the three provinces were significantly higher than that of the past years, which lead to carbon emissions increase.

For the backward “CO\textsubscript{2} emission positive effect”, they increased a lot in January to February 2020 compared to December 2019 in all provinces in China, with the largest “CO\textsubscript{2} emission positive effect” in Guangdong (17.04 million tons), Jiangsu (12.75 million tons) and Shandong (12.23 million tons). Then they decreased month by month,
and the difference among different provinces were less than that of forward “CO\textsubscript{2} emission positive effect”. In May 2020, forward “CO\textsubscript{2} emission positive effect” on Jilin (−0.03 million tons) and Gansu (−0.19 million tons) changed to be negative, which indicates CO\textsubscript{2} emissions driven by these provinces increased. This is due to the growth rate of economic added value of Processing of Petroleum, Coking, and Processing of Unclear Fuel (S4) in the two provinces increased significantly compared with the past three years. CO\textsubscript{2} emissions have risen significantly, so the “CO\textsubscript{2} emission positive effect” in the two provinces in May was negative.

4.3. Screening of key sectors for CO\textsubscript{2} emissions reduction

4.3.1. Screening principle

In order to choose key sectors which can reduce CO\textsubscript{2} emissions but not affect the development of economy, the screening principle combined both the aspects of economic development and CO\textsubscript{2} emissions reduction together. Due to the different scenarios, the key sectors are selected in the epidemic serious period (Fig. 7a) and economy recovery period (Fig. 7b) separately at first.

As for the epidemic serious period, because there is great decrease both in economy and CO\textsubscript{2} emissions, so “economic negative effect” and “CO\textsubscript{2} emission positive effect” are set as horizontal and vertical coordinates, and the origin is the average values of these two factors. If a sector is located at the second quadrant, it indicates that the “economic negative effect” of the COVID-19 on it is below the average of national average level, while the “CO\textsubscript{2} emission positive effect” is above the average of national average level. This sector can be seemed as key emission reduction sector, because it has big CO\textsubscript{2} emission reducing potential but has little influence on economy development. On the opposite, if a sector is located at the fourth quadrant, it can be seemed as key development encouraged sector, since it has a little of CO\textsubscript{2} emission reducing potential but has large influence on economy development.

As for the economy recovery period, due to the implementation of some national policies, economy and CO\textsubscript{2} emissions grew at the same time. In such scenario, economic linkage and CO\textsubscript{2} emission linkage are set as horizontal and vertical coordinates. And the origin is the average values of these two factors. If a sector is located at the second quadrant, it indicates that the economic linkage of this sector is below the average of national average level, while the CO\textsubscript{2} emission linkage of this sector is above the average of national average level. This sector can be regarded as key emission reduction sector, because it only increases less economy growth but brings about higher CO\textsubscript{2} emissions. On the opposite, if a sector is located at the fourth quadrant, it can be seemed as key development encouraged sector, because with the development of economy, there is less CO\textsubscript{2} emission driven or impulse by this sector even though there’s higher economy growth driven or impulse by it.

Due to the different policy implications based on forward linkage and backward linkage, key sectors are screened separately. Further, in order to select the ultimate key sectors for CO\textsubscript{2} emission reduction, the key sectors selected in two periods need to be taken the intersection. Key emission reduction sectors are these which with less economic decline and higher carbon emissions reduction during epidemic serious period, while with higher economic growth and less carbon emission increase during economic recovery period. That is, the sectors in the second quadrant both in Fig. 8a and Fig. 8b are the most important key emission reduction sector, while that in the fourth quadrant both in Fig. 8a and 8b are the most important key development encouraged sectors.
4.3.2. Screening of key sectors based on forward linkage

With the principle mentioned above, key sectors were screened in two periods as shown in Fig. 8a and b. In each period, 13 sectors in 30 provinces were classified into four categories. Based on forward linkage, key emission reduction sectors during the epidemic severe period were Production and distribution of electric power and heat power in Inner Mongolia (P5S8), and Liaoning (P6S8); Processing of petroleum, coking, processing of nuclear fuel in Guangdong (P19S4), and Inner Mongolia (P5S4) and so on. The “economic negative effect” of these sectors were lower than the average level of all sectors, but the “CO₂ emission positive effect” of them were higher than the average level of all sectors. It indicates that although the economic losses on national economy caused by these sectors were not high, the reduction in national CO₂ emissions was very high. This is because both petroleum processing and coking production in Guangdong rank among the top of all provinces in China (National Bureau of Statistics of China). At the same time, the carbon emission per unit of output of petroleum processing (P19S4) in Guangdong was high, so the carbon emission reduction caused by the demand change of its downstream sector after the COVID-19 impact was also large. Processing of petroleum, coking, processing of nuclear fuel (S4) was negatively affected by the drop in international crude oil prices from January to March 2020 (Beijing Institute of Technology Energy and Environmental Policy Research Center, 2020), and Inner Mongolia was also affected. And due to the high CO₂ emission intensity, Processing of petroleum, coking, processing of nuclear fuel in Inner Mongolia (P19S4) therefore drove a larger reduction in CO₂ emissions from downstream sectors. In the case of industry contraction, they had large CO₂ emission reduction potential but low national economy losses, so they were regarded as key emission reduction sectors.

On the contrary, key development encouraged sectors during the epidemic severe period were Other Industries in Shandong (P15S10), and Shanghai (P9S10); Wholesale, Retail Trade and Catering Services in Jiangsu (P10S11), and so on. In 2019, the number of national-level “green factories” in Shandong was at the forefront of the country (Ministry of Industry and Information Technology of the People’s Republic of China, 2019) Information Technology of the People’s Republic of China, 2019). This shows that Shandong’s industrial low-carbon production level has been in the leading position in the country to a certain extent, and the CO₂ emission per unit output is low. Therefore, in the epidemic severe period, although the economic linkage loss to the downstream was large, the reduction of CO₂ emissions induced by it was small. As for Shanghai, the implement of “Shanghai Green Manufacturing System Construction Implementation Plan (2018–2020)” makes the CO₂ emission per unit output of Other Industries in Shanghai (P9S10) lower than the average level.
(Shanghai Municipal Commission of Economy and Information Technology [2018] 427), so the loss of its CO$_2$ emission linkage was also smaller. As for Wholesale, Retail Trade and Catering Services in Jiangsu (P10S11), due to the lower CO$_2$ emissions per unit of output, even though the economic linkage loss during COVID-19 was great, the reduction in CO$_2$ emissions driven downstream was small. Due to their limited carbon reduction capacities, these sectors were regarded as key development encouraged sectors.

During the economy recovery period in Fig. 8b, key emission reduction sectors were Processing of petroleum, coking, processing of nuclear fuel in Processing of petroleum, coking, processing of nuclear fuel in Inner Mongolia (P5S4), Jiangsu (P10S4), and Xinjiang (P30S4); Production and distribution of electric power and heat power in Inner Mongolia (P5S8), and Xinjiang (P30S8), and so on. The economic linkages of these sectors were lower than the industry average, but the carbon emission linkages were higher than the industry average. For Processing of petroleum, coking, processing of nuclear fuel (S4), the CO$_2$ emission per unit output was relatively high. In addition, the petroleum processing and petroleum coke production in Inner Mongolia, Jiangsu and Xinjiang were in the forefront of the country (National Bureau of Statistics of China), and the downstream sectors had greater demand for Processing of petroleum, coking, processing of nuclear fuel in Inner Mongolia (P5S4), Jiangsu (P10S4), and Xinjiang (P30S4). Therefore, during the economic recovery period, Processing of petroleum, coking, processing of nuclear fuel in Jiangsu (P10S4), and Xinjiang (P30S4) pushed the downstream sector to produce more carbon emissions. Inner Mongolia ranked first in electricity generation in 2020 (National Bureau of Statistics of China), and downstream sectors had a large demand for Processing of petroleum, coking, processing of nuclear fuel in Inner Mongolia (P5S4). Thus, it boosted the downstream sectors during economic recovery period to produce even greater carbon emissions. Xinjiang’s natural gas output ranked among the top in China (National Bureau of Statistics of China), and downstream sectors had greater demand for Processing of petroleum, coking, processing of nuclear fuel in Xinjiang (P30S4). Therefore, the increase in carbon emissions from the downstream sector was even more significant. It indicates that these industries brought about large CO$_2$ emissions growth but little economy growth in China. Therefore, they were set as key emission reduction sectors during the economy recovery period.

On the contrary, key development encouraged sectors during the economy recovery period were Other Industries in Anhui (P12S10), and Henan (P16S10); Manufacture of chemical products in Jiangsu (P10S5), and so on. On account of some special programs put into effect in Other Industries in Anhui (P12S10) (Anhui Provincial Department of Economy

![Fig. 10. Key sectors selected based on forward (hollow) and backward (solid) linkage. The sectors in red are key emission reduction sectors, and that in green are key development encouraged sectors.](image-url)
and Information Technology, 2019) and in Henan (P16S10) (Department of Ecology and Environment of Henan Province, 2019), as well as Manufacture of chemical products in Jiangsu (P10S5), CO₂ emissions in these sectors increased relatively lower in the economy recovery period.

4.3.3. Screening of key sectors based on backward linkage

As for the screening of key sectors based on backward linkage, key emission reduction sectors during the epidemic severe period (Fig. 9a) were Processing of petroleum, coking, processing of nuclear fuel in Hubei (P17S54), Production and distribution of electric power and heat power in Hubei (P17S58), and so on. The key development encouraged sectors during the epidemic severe period were Construction in Guangdong (P19S9), Other Service Sectors in Beijing (P1S13), and so on. For Construction in Guangdong (P19S9), Guangdong issued the “Guangdong Province Green Building Action Plan (2013–2020)”, which reduced the carbon intensity of Construction in Guangdong (P19S9) (The people’s Government of Guangdong Province, 2013). In the epidemic severe period, the loss of economic linkage was serious, but the carbon emission linkage reduction was less, so it was not an emission reduction sector. For Other Service Sectors in Beijing (P1S13), the “Beijing 13th Five-Year Plan Period Energy Conservation and Consumption Reduction and Climate Change Plan (2016–2020)” proposed measures to expand green and low-carbon service sectors and cultivate energy-saving and low-carbon service sectors (The people’s Government of Beijing, 2016), so the sector was not a sector that needs to focus on carbon emission reduction.

While during the economy recovery period (Fig. 9b), key emission reduction sectors were Processing of petroleum, coking, processing of nuclear fuel in Guangdong (P19S4), Production and distribution of electric power and heat power in Guangdong (P19S8), and Shandong (P1S58), and so on. Since the oil processing and petroleum coking production of Guangdong were at the forefront of China (National Bureau of Statistics of China), and the power generation of Guangdong and Shandong were both among the top three in China (National Bureau of Statistics of China), the increase in carbon emissions due to increased demand for its upstream sectors during economy recovery period were also large. Key development encouraged sectors during the economy recovery period were Other Service Sectors in Jiangxi (P14S13), Wholesale, Retail Trade and Catering Services in Shandong (P1S511), Other Service Sectors in Xinjiang (P30S13), and so on. From March to May 2020, Jiangxi’s internet and related services saw revenue growth of 24.6 percent (Jiangxi Provincial Bureau of Statistics, 2020), while its CO₂ emissions intensity was relative low. Therefore, Other Service Sectors in Jiangxi (P14S13) had not seen much growth in carbon emissions while the economy was recovered. In the first half of 2020, the retail sales of physical goods in Shandong increased by 14.3% (Shandong Provincial Bureau of Statistics, 2020b), and the CO₂ emission intensity was low, so the return to economic growth was accompanied by lower carbon emissions. From April to May 2020, the CO₂ emissions of Other Service Sectors in Xinjiang (P30S13) was about 0.5 million tons, which was at the downstream level in all provinces (Wang et al., 2020), so it was a sector that needs to be encouraged for development.

4.3.4. Screening of key sectors combing two periods

Further, in order to select the most important key sectors for CO₂ emission mitigation, key sectors in two periods were taken the intersection as shown in Fig. 10 based on forward linkage (in hollow) and backward linkage (in solid) separately. It is shown in Fig. 10, key emission reduction sectors were mostly Processing of petroleum, coking, processing of nuclear fuel (S4), and Production and distribution of electric power and heat power (S8). Although Processing of petroleum, coking, processing of nuclear fuel (S4) had been negatively impacted by the drop in international crude oil prices, the surge in market demand for masks during the COVID-19 period brought about an increase in demand of its products (Beijing Institute of Technology Energy and Environmental Policy Research Center, 2020). In terms of Production and distribution of electric power and heat power (S8), in addition to the temporary drop in electricity demand in China in the first quarter, electricity demand had gradually increased in the following months (International Energy Agency, 2020). Moreover, the CO₂ emission intensities of these two sectors themselves were relatively higher, so CO₂ emissions increase brought about by them was more than other industries. Such as Processing of petroleum, coking, processing of nuclear fuel in Guangdong (P19S4), Production and distribution of electric power and heat power in Inner Mongolia (P5S8) and Liaoning (P6S8), because their production and demand were among the highest in China, driving the downstream sectors and driving the upstream sectors to produce greater carbon emissions, they had greater CO₂ emission reduction potential.

While key development encouraged sectors were mostly Other Industries (S10), Other Service Sectors (S13), and Wholesale, Retail Trade and Catering Services (S11). Other industries (S10) are composed of several industrial sub-sectors, in which metal products maintenance, instrument manufacturing, furniture manufacturing had lower carbon emission intensities, while textile industry, metal products, and communication equipment manufacturing had higher carbon emission intensities. And the composition of industrial sub-sectors in different provinces was also inconsistent, resulting in low carbon emission intensities of Other Industries (S10) in Shandong, Shanghai, Anhui, Henan, and so on. Therefore, carbon emissions in these sectors did not increase significantly when the economy grew sharply. For Other Service Sectors (S13) and Wholesale, Retail Trade and Catering Services (S11), on the one hand, their carbon emission intensities were low so their carbon emission reduction potential was small; on the other hand, during epidemic severe period, offline business activities were affected and difficult to carry out, leasing and commercial services were impacted, and real estate sales were suspended. From January to March 2020, there was negative growth. Therefore, they were sectors that need to be encouraged.

It can also be seen that, key sectors based on forward linkage were much more than that based on backward linkage. This is because the key sectors during two periods based on backward linkage were different a lot and there were only 7 common key emission reduction sectors and 2 key development encouraged sectors. Thus, it is efficiency to take some measures from the upstream of the industrial chain. For example, providing their downstream sectors the inter-mediate products with high added value and low CO₂ emissions.

5. Conclusions and policy implications

5.1. Conclusions and limitations

Weighted Multi-regional Hypothetical Extraction Method (WMHEM) was put forward in this study for the first time, and applied to investigate not only the economic positive effects but also CO₂ emission negative effects during COVID-19 in China. Then, key industrial sectors are analyzed based on inter-sector linkages concluding positive economic effect and negative CO₂ emission effect in this paper.

Firstly, at the industrial scale, the forward and backward “economic negative effect” of Agriculture, Forestry, Animal Husbandry and Fishery (S1) were the least and negative, but the absolute value decreased in April and May. It was the only industry which got economy increased, and pushed the added value increase for the whole industrial chain. As for “CO₂ emission positive effect”, Processing of petroleum, coking, processing of nuclear fuel (S4), its forward and backward “CO₂ emission positive effect” were negative during December 2019 to February 2020, then it increased to be the most in March, and then decreased in April, and to be negative value again in May. It means that, at the beginning of the COVID-19, this industry had much CO₂ emissions linkage; due to the COVID-19, both its forward and backward CO₂ emissions linkage was affected a lot but it can recover easily and had large CO₂ emission potential.
Secondly, at the provincial level, as for overall “economic negative effect”, there was a little of effects in December, but they increased in the whole country from January 2020, while the largest “economic negative effect” appeared in Hubei, Guangdong, Shandong, Jiangsu, Zhejiang and Henan, and then decreased in the following months. Forward “economic negative effect” increased in all provinces from January 2020, with Hubei being the largest, followed by Shandong and Guangdong. Backward “economic negative effect” began to occur in all provinces from January 2020, of which Hubei being the largest which followed by Guangdong, Jiangsu, and Zhejiang, and then they decreased month by month.

Thirdly, at the provincial sectoral level, key emission reduction sectors were mostly Processing of petroleum, coking, processing of nuclear fuel (S4), and Production and distribution of electric power and heat power (S8), while key development encouraged sectors were Guangdong, Jiangsu, and Zhejiang, and then they decreased month by month.

There are also some limitations in the study. Firstly, because the limitation of monthly CO\(_2\) emission data of each industry in all provinces, the article only studied from December 2019 to May 2020. Due to the multiple outbreaks of COVID-19 in different provinces in 2021 and 2022, some provincial sectors may push their upward and downward sectors to reduce more CO\(_2\) emissions. Thus, a few important carbon reduction sectors may be ignored by this study, even though the most important carbon reduction sectors have been identified already. Secondly, there are no official monthly economic added value database. So that the data adopted in the study are collected and arranged from National Bureau of Statistics, Ministry of Transport, Bureau of Statistics of each province. Thirdly, the aggregation degree of the industrial sectors for the noncompetitive MRIO table also affect the uncertainty of the results (Nan et al., 2017; Su and Ang, 2012). In addition, due to the time delay of data publication in China’s Inter-regional Input-Output Table (MRIO), there is no MRIO table in 2020, so the table in 2017 is adopted in this study, assuming that the economic structure relationship remains unchanged. More complete studies could be conducted in the future with more comprehensive results if newer data are available.

5.2. Policy implications

In order to reduce the CO\(_2\) emissions during the development of economy, several policy implications are put forward based on the results of the study.

1. Policy makers should not only pay attention to the direct CO\(_2\) emission industries but also the indirect industrial sectors. The measures to control CO\(_2\) emissions mainly focus on end-of-pipe emission control and apply more pressure to the last section. Every industrial sector is not only a producer, but also a consumer, and every industrial sector needs energy to complete the production process. The growth of consumption of these demand sectors may drive the output of high-emission sectors, so it is urgent to deploy technology and management measures in advance. Not only should we pay attention to those sectors with high direct CO\(_2\) emissions, those sectors that have high demand CO\(_2\) emissions should be considered to improve the energy-saving technology, thereby reducing the intermediate demand for high-emission sectors.

2. It is necessary to study the economic effects and CO\(_2\) emissions effects among regional industries before the adjustment of industrial structure in China, and take carbon emission reduction actions as a board of chess at the national level. As for the screening of key CO\(_2\) emission reduction sectors, it is necessary to combine the “economic negative effect” with the “CO\(_2\) emission positive effect”, to identify key sectors at the provincial level, which can provide more accurate policies and measures for the national carbon emission reduction.

(3) According to the difference between forward and backward linkage, corresponding countermeasures are proposed for key emission reduction sectors respectively as follows:

For forward key emission reduction sectors: reducing their impetus of CO\(_2\) emissions to downstream sectors. Firstly, cutting down the direct CO\(_2\) emission in its production process through technological progress by improving energy efficiency and reducing energy consumption. Secondly, adjusting the production structure of products, and providing the downstream products with high added value and low carbon emissions (Jackson et al., 2022).

For backward key emission reduction sectors: reducing their driving forces of CO\(_2\) emissions to upstream sectors. Firstly, limiting the scale of its demand of carbon-intensive products from upstream sectors and improving the utilization of raw materials. Secondly, optimizing the low-carbon consumption structure, reducing the consumption of high-carbon products, using low-carbon raw materials and intermediate inputs, and giving priority to the purchase of products with low-carbon labels to force the promotion of low-carbon technologies (O’Garra and Fouquet, 2022).

CRediT authorship contribution statement

Wen Wen: Formal analysis, Conceptualization, Resources, Writing - original draft. Yueyang Li: Visualization, Data curation, Methodology, Resources, Writing - original draft, Writing - review & editing. Yu Song: Conceptualization, Supervision, Formal analysis, Methodology, Resources, 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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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