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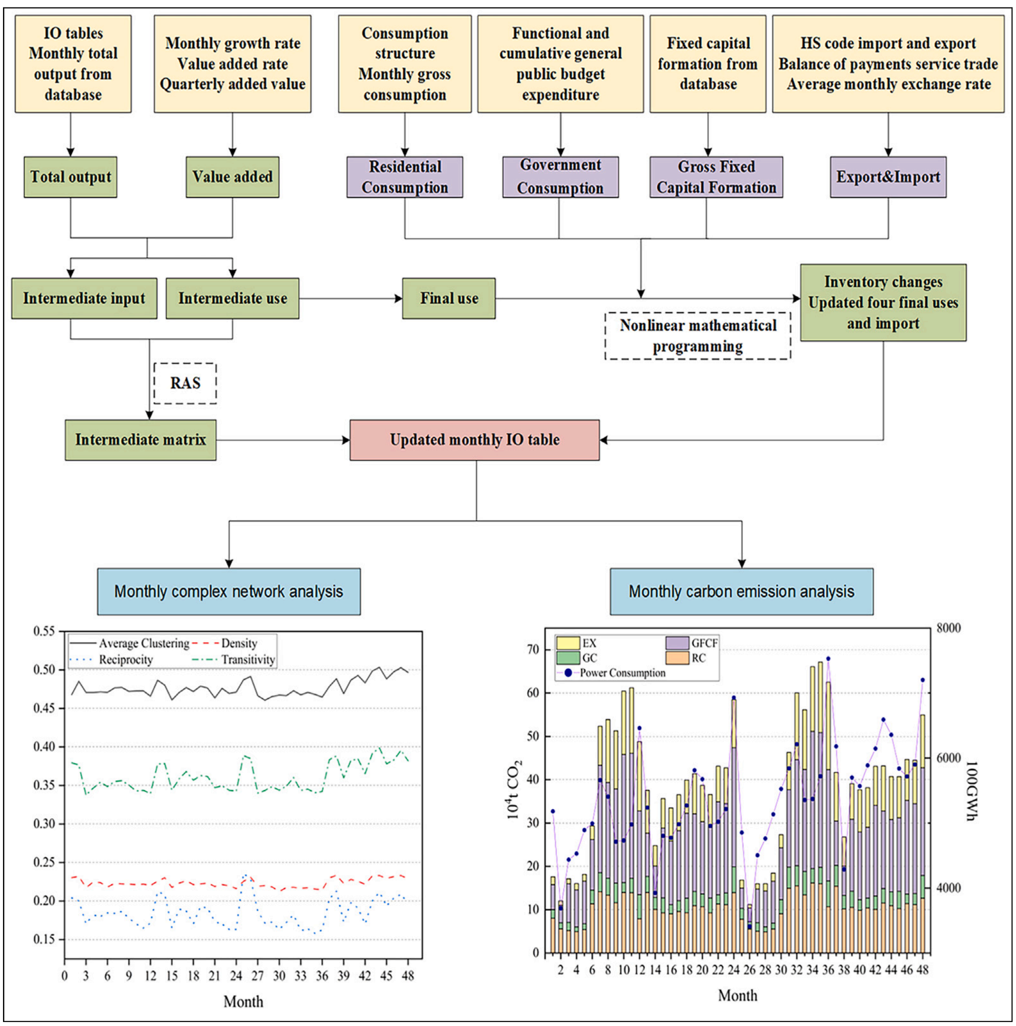

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Highlights

The paper constructs China Monthly Input-Output Database for 2018–2021

The monthly tables' value in revealing monthly sectoral emission changes is presented

Consistency analysis shows well-accuracy performance of the monthly input-output tables

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High-frequency sectoral carbon and environmental analysis based on monthly input-output tables compilation during 2018–2021

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SUMMARY

This paper proposes a process for updating monthly input-output tables with monthly macroeconomic statistics and published input-output tables. Reasonable assumptions are set up and 48 monthly input-output tables are prepared from 2018 to 2021 with the combination of the row range series method and nonlinear mathematical planning. The Weaver-Thomas composite index is used to analyze the role of the sector in the economic network, and the sectoral correlation indicators are used to analyze the correlation change of the sector's monthly electricity emissions to show an environmental application effect of the monthly input-output table. The results show that the monthly input-output tables can be prepared with acceptable accuracy, and they can reveal the sectoral network structure changes and sectoral carbon emissions changes in continuous monthly time series. The proposed approach contributes for the compilation of high-time-frequency input-output tables, so as to support high-frequency industrial environmental impact analysis.

INTRODUCTION

The input-output table is an efficient tool for reflecting the linkages between inputs and the utilization of products across economic sectors. Combined with sectoral environmental accounts, they can be used to analyze the environmental impacts of productive activities in economic sectors. They are now widely used to study economic and environment-related issues. Examples include the use of input-output tables to analyze sectoral energy consumption,[1] carbon emission,[2] virtual water,[3] and the integration of complex network analysis methods to study sectoral linkages.[4] China's input-output tables are typically updated every five years, with the last digit of the year is 2 or 7. In recent years, China has started to update input-output tables for intermediate years, such as 2015 and 2018. Due to the long interval between the publication of the input-output table and the usual delay in its publication (it often takes two or three years to be published), there are uncertainties in data between publication years, and a delay in research development. For effective decisions, it is important to use available quarterly or monthly data to provide insights into the dynamics of environmental stress over time in key sectors.[5] With the rapid development of China's economy, the economic environment has improved the timeliness requirement of government policymaking, and more frequent input-output data are needed to support decision-making.

Some scholars have discussed updating input-output tables by various methods to realize the scientific application of continuous input-output tables. Avelino (2017)[6] used a T-EURO method based on quarterly gross domestic product (GDP) data to update Brazil's annual input-output table from 2004 to 2006; the result found that agriculture changed more in quarterly input-output data than manufacturing and services, and the author believes that the T-EURO method performed better in this case than the row range series (RAS) method, although the results could not be generalized. Zheng et al. (2018)[7] used the matrix transformation technique to update China's input-output table 1992–2020, aiming to focus on future input-output table forecast updates. Zhang et al. (2021)[8] have compiled a continuous annual series of input-output tables for China from 1981 to 2018 using various statistical data published by the National Bureau of Statistics and government sectors, combined with the key coefficient method and the RAS method. Beaufils and Wenz (2022)[9] proposed the scenario-based project of the international trade network method, which combines input-output inverse matrices and RAS methods to predict the global multi-region input-output table. The authors argue that the limitation of this approach is that it does not simulate the behavior of economic agents but rather adjusts the input-output tables to predetermined GDP and trade development scenarios. Liu et al. (2022)[10] updated continuous series of input-output tables for China from 2010 to 2019 by using the RAS method and value-added rates. Yang et al. (2022)[11] performed quarterly

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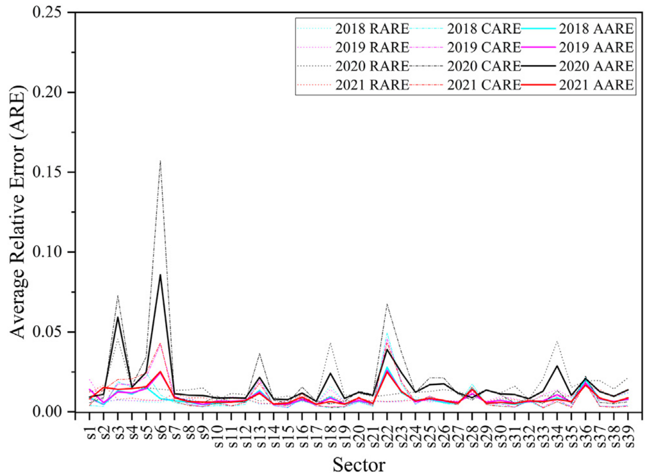

Figure 1. Row average relative error (RARE), column average relative error (CARE), and aggregate average relative error (AARE) by sectors

estimates of sectoral intermediate inputs, value added, end use, and exports using a high-dimensional dynamic factor model based on adaptive sparse principal component analysis, combining RAS methods to predict a complete input-output table ultimately.

Some databases are updating their input-output tables, such as Eora MRIO, which gives China input-output tables from 1990 to 2016.[12] World Input-Output Database provides China's input-output tables from 1995 to 2014;[13] both its initial estimation matrix and its control indicators were obtained using an interpolation or weighted average of the annual supply tables for the two endpoints known to be produced in the region.[14] The third version of the EXIOBASE database provides a multi-region input-output table for 44 countries (28 European Union members plus 16 major economies) and five rest of the world regions each year.[15] These databases estimate the input-output table in China to construct the global input-output table, and their sequential table features differ from the input-output table in China.

Most current input-output table update works focus on the mathematical method of input-output table forecast or annual update tables; however, more frequent work, such as quarterly and monthly input-output table updates, is still lacking. China's high-frequency macro database is becoming more complete, and the official input-output extension tables are becoming more and more regular, which supports the preparation of input-output tables with higher time frequencies. The compilation of higher time-frequency input-output tables such as monthly tables, besides filling the gap that the annual input-output table does not reflect structural changes of a high-frequency continuous time series, it also provides a clearer picture of changes in sectoral environmental pressure when combined with the sectoral monthly environmental accounts. Compared with the annual input-output tables, the higher time-frequency input-output tables can help policymakers grasp the changing patterns of environmental accounts from a continuous time series, thus formulating environmental policies with different time characteristics to effectively control the deterioration of environmental problems. Additionally, it can be further combined with econometric forecasting models to realize immediate projections of future input-output tables, which are of analytical value for the sectoral economic and environmental issues.

Understating the importance of input-output tables as data source for scientific research and decisions, and recognizing that a five-year publications period is too large and brings a temporal gap of knowledge, this paper attempts to complete the frequency enhancement of the monthly input-output tables from 2018 to 2021 by combining RAS, linear interpolation, and nonlinear programming method and using the current monthly macroeconomic database and officially published input-output tables of 2018 and 2020. This paper proposes to innovate in the following two points: (i) Firstly, based on the existing input-output table and the characteristics of the collected monthly macroeconomic data, reasonable data assumptions and processing are made, the RAS method, linear interpolation, and nonlinear programming method then used to prepare 48 monthly input-output tables from 2018 to 2021 based on ensuring the accuracy and reliability of the data; (ii) Secondly, the complex network analysis method is used to demonstrate the monthly sectoral structure changes and the application of monthly input-output tables to analyze monthly sectoral carbon emission changes is presented by using a backward and forward environmental association method. Based on the data continuity and the significant contribution of electricity consumption to China's carbon emissions,[16] this paper uses sectoral electricity consumption data as an example to complete monthly input-output electricity carbon emissions analysis.

RESULTS

Tabulation errors and monthly sectoral relationship changes

The mean relative errors are presented in Figure 1 based on the intermediate consumption matrix differences between the sum of monthly input-output tables and annual tables. Except for S6-Mining Ancillary Activities and Other Mining Products, whose average relative error is larger across sectors due to its partial data deletion, the average relative error across sectors is small (less than 5%). These results show that the monthly input-output table solved by the RAS method can match the annual input-output table well, and the intermediate input-output

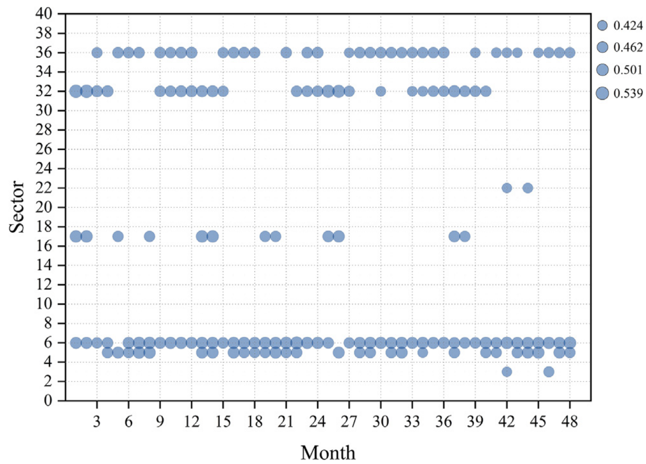

Figure 2. The top three sectors with monthly inward relative closeness centrality, 2018.1–2021.12

structure invariance hypothesis can ensure that the monthly input-output structure of the monthly input-output table is similar to that of the annual input-output table.

Based on monthly input-output tables, Figure 2 shows the results of the first three sectors with the largest inward relative closeness centrality (IRCC) in each month; we analyze the results with the intermediate consumption matrix. It can be seen that the value of the IRCC listed has changed little; only the top three sectors have changed in some months. S6-Mining Ancillary Activities and Other Mining Products appeared most frequently, indicating its strong and stable direct dependence on other sectors, mainly resulting from a strong dependence on mining equipment in S27-Manufacture of Special-Purpose Machinery (the demand for the product in S27 accounts for an average of over 13% of the total demand of S6 over the four years). S5-Mining of Nonmetallic Ores also has high IRCC values, but mainly in the intervening months of each year (April to August in 2018, April to October in 2019, April, May, July, and August in 2020, April, May, and July to September in 2021), due to its dependence on thermal electricity energy from S33-Production and Supply of Electricity and Steam (the demand for the product in S33 accounts for an average of over 15% of the total demand of S5 over the four years). The high IRCC value of S17-Manufacture of Articles for Culture, Education, and Sports Activities appears in January and February of each year, owing to its product demand from S24-Nonferrous Metal Smelting and Rolling (the S17 product demand for S24 accounts for 15.30%, 15.62%, 15.10%, and 13.15% of its total demand four years, respectively). The IRCC value of S32 Other Manufacture is high at the beginning and end months of the previous three years, resulting from its large electricity consumption. The high IRCC value of S36-Construction in 2019 results from its product demand from S22-Manufacture of Nonmetallic Mineral (the S36 product demand for S22 accounts for 22.05% of its total demand).

Changes in the sectoral outward relative closeness centrality (ORCC) are more pronounced than IRCC, as shown in Figure 3. S27-Manufacture of Special-Purpose Machinery appears most frequently, indicating a distinct service attribute supporting productive activities in other sectors. Its service's intensity and stability are stronger than other sectors. Bubbles of major service sectors (S32–S38) were sprinkled throughout the month, indicating the strong service characteristics of these sectors. In the former half of 2018, the ORCC value of S6-Mining Ancillary Activities and Other Mining Products is prominent, owing to its extensive services to S3-Extraction of Crude Petroleum and Natural Gas (the service input into S3 accounts for over 75% of its total amount), while in the latter half of 2018, S18-Manufacture of Refined Petroleum, Coke Products, Processing of Other Fuel has high ORCC value from providing transport services to S38-Transport, Storage, and Post (the input into S38 accounts for over 20% of its total amount). In 2019, the ORCC of S9-Tobacco Products is high because it inputs large tobacco products into S39-Other Service Industries in May and July (the input into S39 accounts for 19.58% and 21.67% of its total amount). S2-Ming and Washing of Coal and S6-Mining Ancillary Activities and Other Mining Products have high ORCC in the second half of 2020, mainly due to their provision of products to S33-Production and Supply of Electricity and Steam and S3-Extraction of Crude Petroleum and Natural Gas, respectively (the input from S2 to S33 accounts for over 30% of its total amount, while the input from S6 to S3 accounts for over 80% of its total amount). In 2021, S9-Tobacco Products (after March) and S19-Chemical Raw Materials and Products (in the first half year) have high ORCC, it is because S9 mainly put products into S39 (the input into S39 accounts for over 15% of the total amount of S9) while S19 was dominated by the resources distribution of resources among its sub-sectors (the input into itself accounts for over 30% of its total amount).

Figure 4 shows the top three sectors with the largest relative betweenness centrality (RBC) in different months. It can be seen that the sectors with prominent intermediary roles are concentrated in sector 19-Chemical Raw Materials and Products, S38-Transport, Storage and Post, and S39-Other Service Industries. The three sectors serve as bridges in the sectoral economic network, which significantly impact the sectoral relationships and input-output activities. Especially, the RBC of S19 significantly increased in 2021, indicating there are more services and products flowing through the sector. Although the RBC of S37-Wholesale, Retail Accommodation, and Catering is lower than these three sectors, it remained an important intermediary role in the economic network, which specifically reflected in January, October, November, and December in 2018, February, July, October, and November in 2019, July and September in 2020, and February in 2021. S3-Extraction of Crude Petroleum and Natural Gas showed a strong intermediary effect in June and October 2021, with a high demand for services

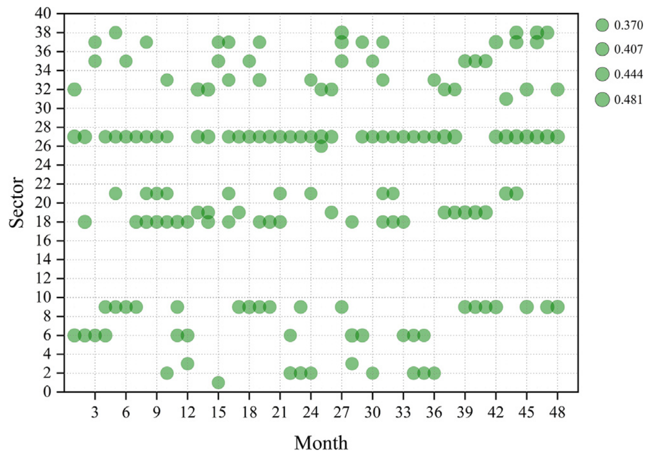

Figure 3. The top three sectors with monthly outward relative closeness centrality, 2018.1–2021.12

from S39-Other Service Industries and a high supply of products for S18-Manufacture of Refined Petroleum, Coke Products, Processing of Other Fuel.

Figure 5 shows the variation of the average clustering, density, reciprocity, transitivity of input-output directed networks, and their trends in the study period are the same. They showed an obvious increase in January 2019, 2020, and 2021, while their value remained high in February. This indicates that there are more supply chain and business cooperation opportunities in the input-output networks in January and February of each year, the market is more responsive, the circulation of products and services within the networks is more efficient, and the linkages between sectors are more stable. In February and March of each year, there were significant declines in all four indicators; this could be the result of supply chain contraction and lower tourism output after the Spring Festival. Businesses also typically make adjustments before the start of the new fiscal year, including strategic adjustments, business restructuring, and workforce changes. These changes also lead to supply chain disruptions and partnership adjustments that reduce the value of the four indicators. Overall, these results reflect the important role of monthly input-output tables in capturing monthly sectoral correlation changes.

Monthly changes in sectoral carbon emissions linkages

The total embodied electricity carbon emissions of four final uses are shown in Figure 6. The variation in total monthly carbon emissions is visually evident, reflecting the value of the monthly input-output tables in revealing the characteristics of high-frequency sectoral environmental pressure changes. Carbon emissions have decreased significantly between December and January of the following year and between January and February of each year. The most significant decrease was between December 2019 and January 2020, with the final use of carbon emissions falling by 416,300 tonnes. Declines in final-use-driven electricity carbon emissions are directly linked to sectoral electricity energy consumption declines. For example, electricity consumption declined by 207.6 billion kWh between December 2019 and January 2020. A consistent trend in total carbon emissions and electricity consumption can also be observed in Figure 6, and the total emissions are generally

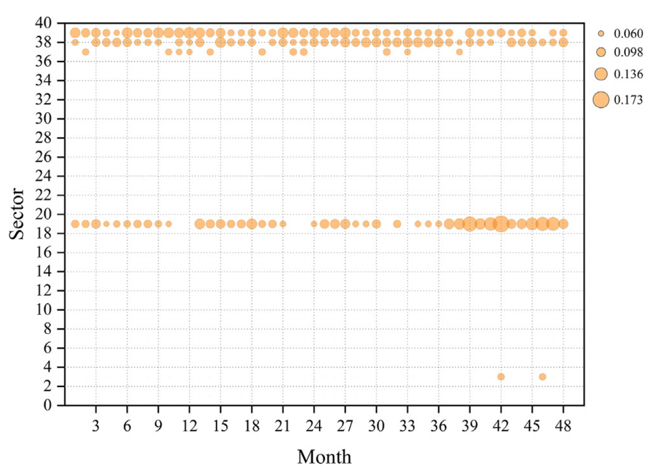

Figure 4. The top three sectors with monthly relative betweenness centrality, 2018.1–2021.12

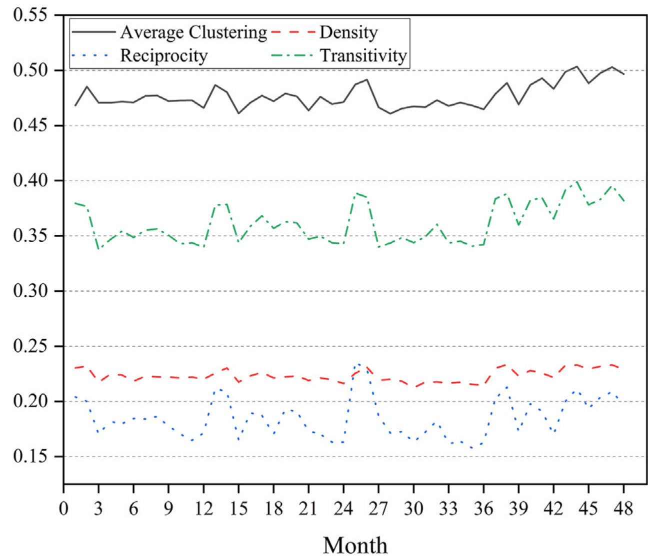

Figure 5. Average clustering, density, reciprocity, transitivity in sectoral network, 2018.1–2021.12

higher in the second half of each year. In final uses, the gross fixed capital formation (GFCF) has the largest emissions, contributing 42.59% of total emissions, followed by residential consumption (RC), with an average contribution of 29%. Exports (EX) ranked third with a contribution of 19.69%, with the smallest contribution being 8.72% of government consumption (GC). The total emission growth in the second half of each year is mainly due to the change in GFCF and RC; therefore, to control electricity carbon emissions, it is efficient and scientific to implement stricter control policies on construction and household electricity consumption in the second half of each year, for the key sectors of GFCF and RC are construction and household sectors.

The marginal carbon emission coefficients under backward (CBLC) and forward (CFLC) linkages are shown in Figure 7. Some sectors have a marginal carbon emission coefficient greater than 1 in few months, such as S15-Manufacture of Paper and Paper Products (CBLC in January of the previous three years) and S18-Manufacture of Refined Petroleum, Coke Products, Processing of Other Fuel (CFLC in January of the latter three years), which suggests that the impact of production and consumption activities of S15 and S18 on overall carbon emissions is significant only in a few months. S33-Production and Supply of Electricity and Steam and S35-Production and Distribution of Water, whose marginal carbon emission coefficients were much higher than 1 each month, always significantly impacted carbon emissions from 2018 to 2021. Specifically, the main products from S33 are electricity and thermal energy; the process of product allocation directly affects the distribution of electrical energy in other sectors; its electricity energy consumption is much higher than other sectors, so it has a significant impact on electricity carbon emissions of other sectors both in its unit product demand and unit product allocation. S35-Production and Distribution of Water has a larger CBLC than its CFLC, suggesting that it generates much higher electricity embodied carbon emissions per unit of product and service

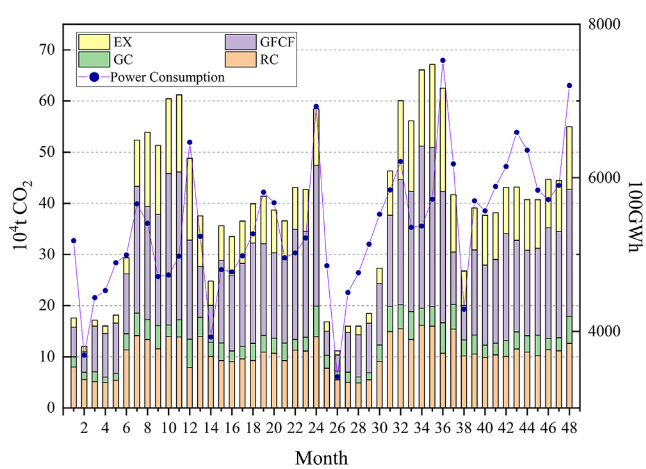

Figure 6. Total embodied electricity emissions of monthly final uses, 2018.1–2021.12.RC: Residential Consumption, GC: Government Consumption, GFCF: Gross Fixed Capital Formation, EX: Export

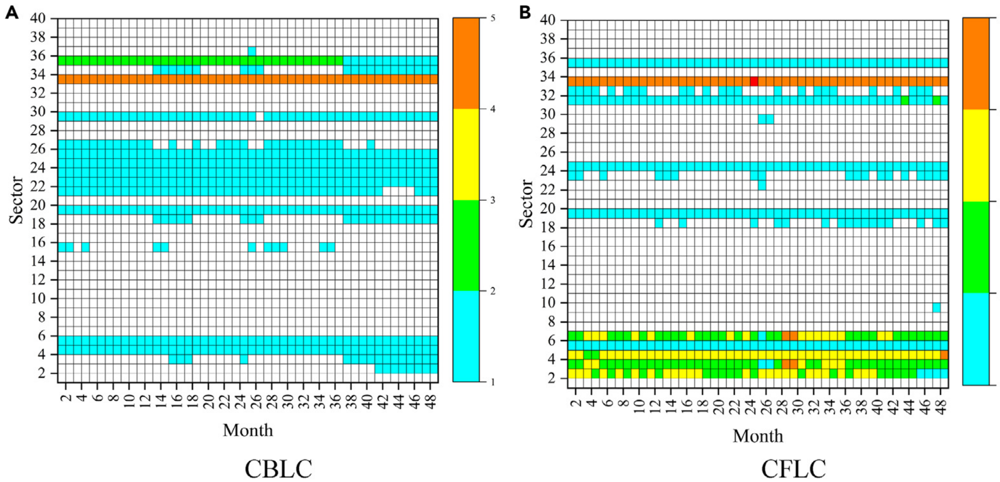

Figure 7. Intersectoral marginal carbon emission indicators under two different linkages, 2018.1–2021.12

(A) Backward linkage.

(B) Forward linkage.

demand in other sectors than the average sectoral level; its production activities should focus on selecting low-carbon products to reduce its contribution to emissions. In addition, S2-Ming and Washing of Coal, S3-Extraction of Crude Petroleum and Natural Gas, S4-Mining of Metal Ores, and S6-Mining Ancillary Activities and Other Mining Products have high CFLC values, so there is a need to focus on optimizing the power consumption structure of the production activities in these mining sectors to reduce the high carbon embodied in their products.

Absolute carbon emission indicators of final uses under backward correlation (BTC) reflect the ratio of embodied electricity carbon emissions driven by sectoral final use to the average level; the results are shown in Figure 8. Among the emissions driven by household consumption (Figure 8A), S7-Agricultural Sideline Food Processing and Manufacturing, S33-Production and Supply of Electricity and Steam, and S39-Other Service Industries have the largest BTC. Since only the GC of S1-Farming, Forestry, Animal Production, and Fishery, S38-Transport, Storage, and Post, and S39-Other Service Industries are non-zero, a large white square appears in Figure 8B. At the same time, S39 has the largest BTC, and the government consumption of services in this sector has caused the largest contribution to carbon emissions. There are also few sectors whose GFCF are not zero, with S36-Construction having the highest BTC value, which is a pillar sector of fixed capital formation and drives much higher electricity carbon emissions than other sectors (Figure 8C). In addition, GFCF of S26-Manufacture of General-Purpose Machinery, S27-Manufacture of Special-Purpose Machinery, S28-Manufacture of Transport Equipment, and S39-Other Service Industries all contributed to higher than average electricity carbon emissions during the study period, while GFCF of S30-Manufacture of Communication Equipment, Computer, and Other Electronic Equipment only contributed to higher than average emissions in the previous three years. Among sector exports (Figure 8D), S30 had the highest BTC value. Its product-driven electricity carbon emissions were significantly higher than other sectors, particularly in March, September to November 2018, September to November 2019, and July, August, October, and November 2020, with 8.5 times the average value of electricity emissions, followed by S29-Manufacture of Electrical Machinery and Apparatus. Therefore, the export of Chinese electronic products will produce a large amount of electricity carbon emissions, particularly during the latter half of each year of the study period.

Figure 9 plots the BTC of the sum of four sectoral final uses (Figure 9A) and the FTC of sectoral value added (Figure 9B). S36-Construction was found to have the highest BTC-TF value, followed by S39-Other Service Industries. S39 also has the largest FTC value, followed by S33-Production and Supply of Electricity and Steam. In order to reduce carbon emissions from electricity, there is a need to focus on optimizing the production structure of the electricity sector and other service sectors, such as optimizing power generation processes in the electricity sector and developing scientific service electricity use plans. In addition, the construction industry can reduce carbon emissions by reducing electricity consumption through energy-efficient measures such as improved insulation, efficient building materials, and heating and air-conditioning. In addition, FTC of S33 and S37 increased significantly after February 2021, well above the average sectoral FTC values, suggesting that additional attention in recent years to the high-carbon segments of production activities in S33 and S37 is needed.

Based on the previously described analysis of sectoral embodied electricity carbon emissions, the monthly input-output tables obtained in this paper are able to capture characteristics of monthly sectoral changes related to carbon emissions. In addition to being directly linked to changes in electricity consumption, sectoral carbon emission changes are associated with production linkages between sectors and the final use demand for sector products. Alternative methods to explore the root causes of carbon emission changes, such as structural decomposition and structural path analysis, are well aligned with input-output tables. The point is that monthly sectoral carbon emissions changes cannot be captured based on existing annual input-output tables alone, while they can be obtained based on the monthly input-output tables, and it is just an application scenario for monthly input-output tables.

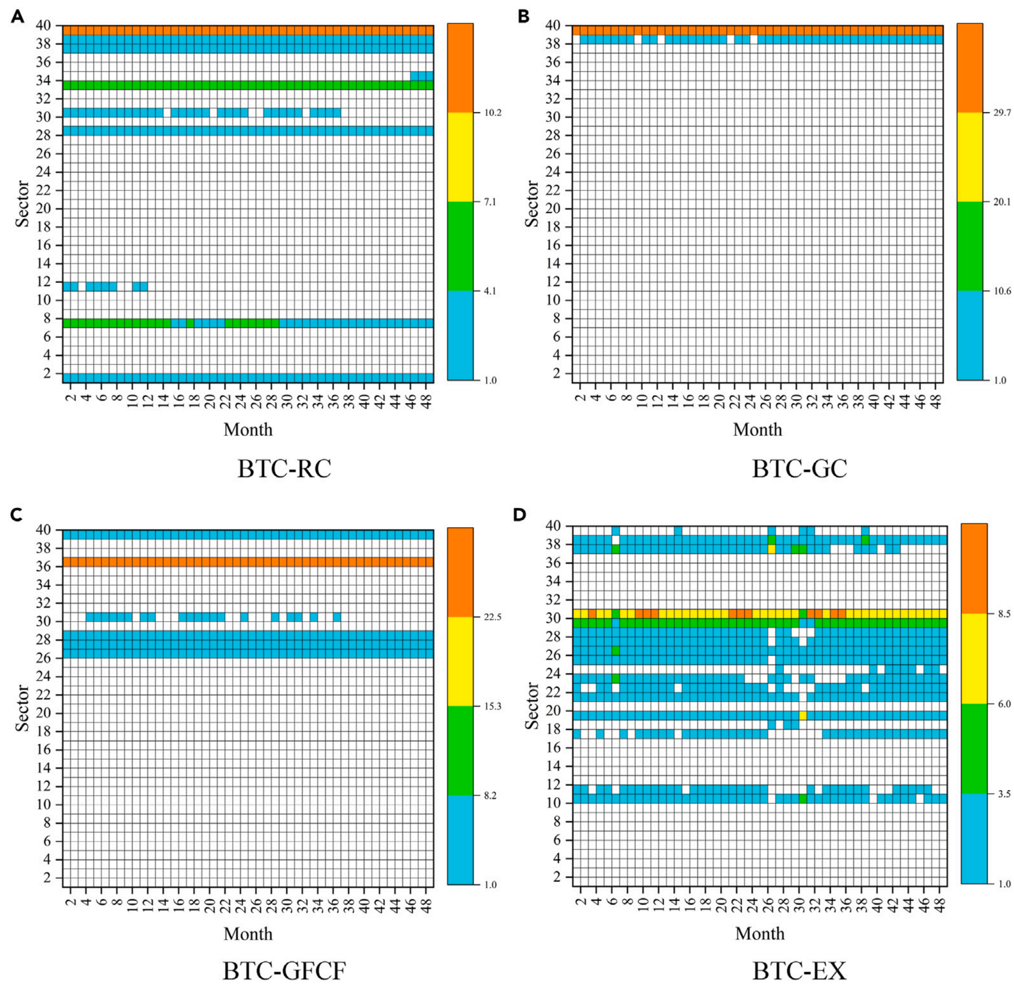

Figure 8. Sectoral absolute carbon emission indicators for final uses under backward correlation, 2018.1–2021.12

(A) Residential consumption.

(B) Government consumption.

(C) Gross fixed capital formation.

(D) Export.

Consistency analysis

Up to now, it is not clear to what extent the updated monthly input-output tables differ from the annual input-output tables in terms of sector carbon emissions, since the RAS method equalization and sectoral carbon intensity both could affect the emission results. So, we have further calculated monthly embodied electricity carbon emissions of final uses and value added by sectors, then added the monthly results to years and compared them with the emissions calculated by annual input-output tables; the relative deviations are shown in Figure 10. The embodied electricity carbon emissions from the previous two calculations deviate little; the deviation is basically maintained within 2% by RC, GC, GFCF, and EX. The emission deviation of total final use ranged from −3.8% to 5.4% (Figure 10E), while the variation of the value added ranged from −0.9% to 5.7% (Figure 10F), suggesting that the updated monthly input-output tables were broadly consistent with the annual input-output tables in terms of total carbon emissions. Additionally, the monthly table could still be used to reflect changes in sector carbon emissions during monthly time series, which supports the application of the environmental analysis of the monthly input-output tables.

DISCUSSION

The 48-month updated input-output tables from 2018 to 2021 was completed in this paper using macro statistics, and the analysis of changes in sectoral economic and carbon emission linkages across months was conducted using a complex network analysis method in conjunction with the sectoral electricity carbon emission account. The results indicate that based on the existing monthly database and the officially published annual input-output table, the average error between the monthly input-output table compiled using the RAS method and the annual

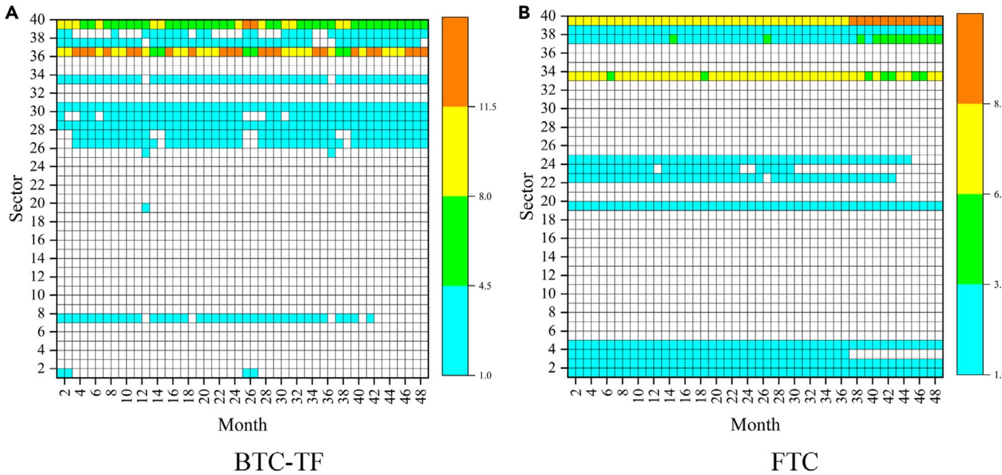

Figure 9. Intersectoral absolute carbon emission indicators under two different linkages, 2018.1–2021.12

(A) Backward linkage.

(B) Forward linkage.

input-output table is less than 5%. When sectoral inventory data are difficult to obtain or differ significantly from inventory changes in the input-output table, focusing on adjusting other final uses and estimating the total final use may be a feasible method. Based on monthly input-output tables, the results of complex network analysis reflect that the key upstream product supply sectors and downstream product consumption sectors changed in months. Although the sectors with the highest betweenness centrality do not change much in consecutive months, the numerical changes reflecting the strength of their intermediary effects still reveal the strength of their impact on the sectoral input-output network in specific months. Compared with traditional annual input-output tables, the sectoral network changes based on continuous monthly input-output data can reflect how sectoral relationships change in consecutive months, which helps to promote the development of the leading sector in a specific month and establish a closer industry chain by leveraging the positioning of key upstream and downstream sectors in each month.

The monthly input-output table also provides a tool for studying how monthly final use drives changes in sectoral environmental pressure, such as sectoral electricity carbon emissions. The monthly input-output table not only helps to form a continuous monthly sectoral carbon emissions database but also identifies sectors that have a significant impact on electricity carbon emissions in specific months. This helps to explore the monthly consumption characteristics of sectors and seek targeted carbon reduction measures, including improving the production efficiency of upstream sectors or optimizing the consumption structure of high-carbon products. The carbon emission results reflect the deviation between the year table added by monthly input-output table and the annual input-output table is basically less than 5%, and the deviation of their final use electricity emission results is less than 6%, indicating that the monthly input-output table obtained has acceptable accuracy.

The continuous time series data formed by the monthly input-output table can be combined with econometric models to predict the sectoral economic structure in the future. By embedding the sectoral environmental account, environmental issues such as carbon emissions can be predicted, which helps to make adjustments in advance for these adverse changes. In a long time series, seasonal or other cyclical changes in the input-output structure among sectors may be found, which helps policymakers take corresponding measures to adjust the sectoral input-output structure at different time periods to make it more favorable for economic development.

The input-output table is a powerful tool for describing the relationship between inputs and outputs across regional sectors, allowing large scope for future applications. In addition to filling the gap in the current annual input-output table, the monthly input-output table may expand research areas such as input-output forecasting and update based on high-frequency input-output data. Although some scholars have paid attention to the update of input-output table in the time dimension, the high-frequency update of input-output table is still limited. This paper provides a method to update high-frequency input-output data according to the actual data characteristics and to highlight the rationality in data processing and setup assumptions; the possible improvement also has revealed and calls for further development in high-frequency updates of input-output table.

Limitations of the study

Admittedly, even if assumptions can be made based on relatively small changes in sectoral data, it is still not a real reflection of actual data and will inevitably lead to computational errors, which need to be adjusted in the future to improve the data accuracy. The input-output update in this paper is based primarily on official input-output tables of 2018 and 2020, with close years leading to similar structures (such as structures in consumption and intermediate use). The interval between the publication of the adjacent input-output tables is five years, which means that the sectoral structure could change greatly during the period, leading to large errors by the application of the linear interpolation. Since the

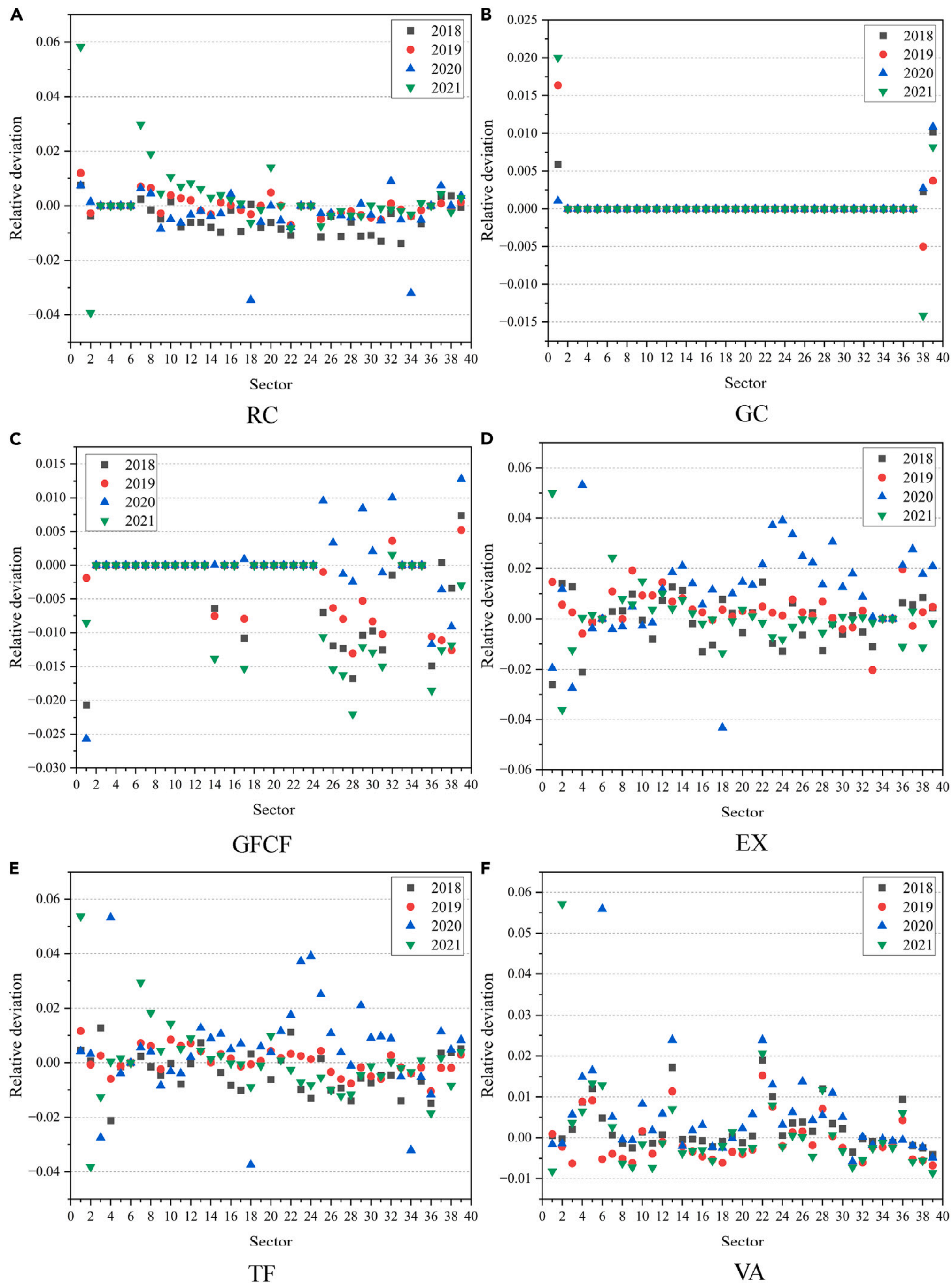

Figure 10. The relative deviation between the sectoral electricity carbon emissions of aggregated monthly final uses and value added with corresponding emissions by years

(A) Residential consumption.

(B) Government consumption.

(C) Gross fixed capital formation.

(D) Export.

(E) Total final use except for inventory changes.

(F) Value added.

technology of updating the current annual input-output table is quite mature,[8] updating the input-output table for the intermediate year using the published official input-output table and updating the monthly input-output table based on the updated continuous annual input-output table may be an effective way to reduce the computational errors. In addition, the data collected for inventory change vary widely both in the same sector in different months or among sectors in the same month. Its changing characteristics are difficult to capture and therefore the treatment of inventory change must be emphasized.

There are several key problems during the data processing of inventory change. Firstly, the sum of the monthly inventory change must be equal to the inventory change in the annual input-output table. Secondly, the update process of sectoral inventory change should set a change range, and whether it is necessary to set a minimum constraint of structural errors needs to be considered. The last problem is how to adjust the monthly inventory change in the year without official input-output tables. In this paper, it is feasible to derive inventory changes by focusing on improving the accuracy of other final use categories, which ensures the sum of monthly sectoral inventory changes is equal to the annual inventory changes, without affecting the constraint conditions for other final uses. In the future, consideration should be given to the use of collected macroeconomic data for the estimation of monthly inventory changes and to ways to further improve the accuracy of other final uses.

Although the RAS method is currently commonly used to update input-output tables, it still has certain limitations. The adjusted input-output structure relies on the existing official input-output tables, which require high data requirements for intermediate inputs and intermediate uses. Therefore, in the future, other algorithms may be required to directly fill in the intermediate input matrix. Some key sectors such as the construction industry have detailed upstream and downstream product consumption data; the estimated intermediate input matrix based on such data may be more accurate than the matrix obtained by the RAS method. On the other hand, it is necessary to focus on exploring the estimation methods of monthly intermediate use and intermediate input to improve their accuracy as the basic variables of the RAS algorithm.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

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SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2023.108045.

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AUTHOR CONTRIBUTIONS

G.Y.L., D.X., and H.L. contributed to methodology development, conducted validation, and contributed to the writing of early drafts and final draft review and editing; G.Y.L. and H.L. were responsible for overall project supervision, conceptualization, and project management; F.X.M., Y.C., F.A., C.M.V.B.A., and B.F.G. contributed to the data analysis and revision checking.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Input-output tables for 2018 and 2020 in China	NBSC(2020), NBSC(2022a)	http://www.stats.gov.cn/sj/
Monthly current and cumulative electricity consumptions of industries	NEA(2022)	http://www.nea.gov.cn/
Monthly sub-functional general public budget expenditure	MFPRC(2022)	http://www.mof.gov.cn/index.htm
Monthly imports and exports of industries	GACPRC(2022)	http://www.customs.gov.cn/
Monthly US dollar exchange rates for RMB	SAFE(2022)	http://www.safe.gov.cn/
Monthly industrial value added growth rate and quarterly value added	NBSC(2022b)	http://www.stats.gov.cn/sj/
Raw data of monthly total output and gross fixed capital formation	Beijing Tengjing Big Data Application Technology Research Institute	http://www.tjresearch.cn/
Monthly inventory data for industrial enterprises	National Bureau of Statistics	http://www.stats.gov.cn/sj/
Data generated by this paper (Monthly sectoral dataset of value added, total output, and final use)	This paper	Data S1

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources should be directed to and will be fulfilled by the lead contact, Gengyuan Liu liugengyuan@bnu.edu.cn.

Materials availability

This study did not generate new unique materials.

Data and code availability

- This paper analyzes existing, publicly available data which are listed in the key resources table. The data generated by our analysis can be found in Data S1.
- Code for the analysis was written in Matlab and is available from the lead contact upon request.
- Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

METHOD DETAILS

Updated monthly input-output table model

This paper uses the existing sectoral annual, quarterly and monthly macroeconomic databases to update the sectoral total output, value added, household consumption, government consumption, gross fixed capital formation, imports and exports, the updating process is shown in Figure S1. The intermediate input and intermediate use are obtained as the column control and row control of the monthly input-output table. The intermediate consumption matrix of the monthly input-output table is obtained by the RAS method in conjunction with the intermediate consumption matrix of the base year. Constraints and target functions were set based on the data characteristics of final use categories and imports. The nonlinear mathematical programming method is used to adjust the final use and imports, resulting in an updated monthly input-output table.

Originally proposed by Stone (1962),[17] the RAS method is commonly used to solve a target period's intermediate consumption matrix based on its base period's intermediate consumption matrix. It updates the intermediate consumption matrix under the constraints of intermediate input and intermediate use of the target period, following the principle of overall optimization.[18,19] For each monthly input-output tables in 2018 and 2020, the monthly direct consumption factor matrix is based on the official 2018 and 2020 input-output tables. For 2019 and 2021, due to the lack of official tables, the input-output structural changes between their preceding and subsequent years are considered. The 2019 input-output tables are solved using a pre-and post-weighted RAS method. Based on the intermediate consumption matrices of the 2018 and 2020 input-output tables, combined with the annual total values of monthly intermediate inputs, intermediate uses, and total outputs in 2019, the RAS method is used to calculate the intermediate consumption matrices, and the average of the two is taken as the annual consumption matrix for 2019. Since there is currently no input-output table for subsequent years in 2021, the intermediate consumption matrix of 2021 is obtained from the matrix of 2020.

The initial iteration number of RAS is set at 50, the composite error values after each row iteration is compared, and the optimal number of iterations is determined based on the minimum error value during the iteration process, thereby obtaining the corresponding optimal intermediate matrix. If the total error of each of the 50 iterations converges from high to low, and the comprehensive error of the last two iterations is less than 0.0001, the the optimal matrix is calculated after the last iteration, otherwise the number of iterations is increased until the comprehensive error value of the previous and subsequent iterations is less than 0.0001. The error value of the iteration process is calculated as follows.

$$URO_i = (RX_i - 1)^2 \tag{Equation 1}$$

$$CRO_i = (SX_i - 1)^2 \tag{Equation 2}$$

$$ARO_i = URO_i + CRO_i \tag{Equation 3}$$

where URO_i, CRO_i and ARO_i is the row error, column error and aggregate error of the i iteration respectively. After monthly input-output tables are prepared, the error analysis is carried out using the average relative error as follows:

$$RARE_i = \frac{1}{nr}\sum_{j=1}^{n}\left|CIM_{i,j} - RIM_{i,j}\right| / RIM_{i,j} \tag{Equation 4}$$

$$CARE_j = \frac{1}{nc}\sum_{i=1}^{n}\left|CIM_{i,j} - RIM_{i,j}\right| / RIM_{i,j} \tag{Equation 5}$$

$$AARE_i = \frac{1}{2}(RARE_i + CARE_i) \tag{Equation 6}$$

where $RARE_i$, $CARE_i$ and $AARE_i$ are the row, column and aggregate average relative errors of i sector, respectively. $CIM_{i,j}$ is the element in row i and column j of the annual intermediate matrix obtained by the addition of monthly matrices, $RIM_{i,j}$ is the element in row i and column j of the annual intermediate matrix of the base year. nr and nc represent the total number of addition terms not meaningless in Equations 4 and 5.

It is difficult to obtain inventory changes by linear interpolation because it represents change values in a period, unlike other final uses at a fixed time. Therefore, we focus on the more accurate values of other final uses. The monthly inventory changes can be obtained by subtracting the total final use value from the full value of other final use categories. Based on the credibility of the initial value of each final uses, a larger deviation is given to exports and imports (imports are not final use, here is just for narrative convenience), and a smaller deviation is given to household consumption, government consumption and gross fixed capital formation. There are sectoral differences in the sources of import and export data, since deviations on them are mainly reflected in sectors within the same month, while trends in individual sectors are more reliable. The opposite is true for household consumption, government consumption, and gross fixed capital formation, as household consumption structure has showed a constant behavior from 2018 to 2020. Only a few sectors have values different from zero for government consumption and fixed capital formation, the sectoral structure changes are also not significant, and the sectoral structure of the three final uses in the same month is more reliable than the time changes of each sector. Thus, for household consumption ($k = 1$), government consumption ($k = 2$) and gross fixed capital formation ($k = 3$), the error is the structural change between sectors at the same time point. In contrast, for exports ($k = 4$) and imports ($k = 5$), the error is the smallest structural change in the same sector over a continuous time series, and the target function is the smallest of the sum of the two errors, as shown in the Equation 7.

$$\min \sum_{t=1}^{12}\sum_{k=1,2,3}\sum_{i=1}^{39}\left|\frac{y_{t,ik}}{\sum_{i=1}^{39} y_{t,ik}} - \frac{y^0_{t,ik}}{\sum_{i=1}^{39} y^0_{t,ik}}\right| + \sum_{t=1}^{12}\sum_{k=4,5}\sum_{i=1}^{39}\left|\frac{y_{t,ik}}{\sum_{t=1}^{12} y_{t,ik}} - \frac{y^0_{t,ik}}{\sum_{t=1}^{12} y^0_{t,ik}}\right| \tag{Equation 7}$$

$$s.t. \quad y_{t,ik} \geq 0 \tag{Equation 8}$$

$$\frac{\left|y_{t,ik} - y^0_{t,ik}\right|}{y^0_{t,ik}} \leq \lambda_1, \left(k = 1,2,3, y^0_{t,ik} \neq 0\right) \tag{Equation 9}$$

$$\frac{\left|y_{t,ik} - y^0_{t,ik}\right|}{y^0_{t,ik}} \leq \lambda_2, \left(k = 4,5, y^0_{t,ik} \neq 0\right) \tag{Equation 10}$$

$$\sum_{t=1}^{12} y_{t,ik} = y_{year,ik} \qquad \text{(Equation 11)}$$

where $y_{t,ik}$ is the updated k final use category of sector i in month t, $y^0_{t,ik}$ is the original k final use category of sector i in month t.

Equation 8 shows the updated nonnegative constraint for all sectors' final use and imports in each month, while Equation 9 is the constraint on relative changes in sectoral household consumption, government consumption, and gross fixed capital formation; λ_1 is the maximum range value of relative variation, assumed as 0.4 in this paper. Equation 10 is the constraint on relative changes in sectoral export and import, λ_2 is also the maximum range value of relative variation, assumed as 0.8 in this paper. Equation 11 is the constraint that the total monthly values of updated sectoral final uses and import equal the annual values.

Characteristics of sectoral networks

After monthly input-output tables are prepared, the variation of monthly sectoral relations is studied using the complete coefficient matrix (the direct coefficient matrix does not fully reflect the product consumption and distribution linkages between sectors). Columns of the complete coefficient matrix reflect a sector's consumption of other sector products, so the backward demand network is built accordingly. Rows of the complete coefficient matrix reflect the distribution of products from one sector to others, so the forward distribution network is built accordingly. The Weaver-Thomas composite index (WT), which is widely used in regional economics to identify and analyze the complexity of different combinations of factors, is used to search for thresholds to build complex sectoral networks. The sequence $e_{1,j}$, $e_{2,j}$,..., $e_{n,j}$ represents n sample values corresponding to the j type of indicator, arrange the sequence in reverse order to obtain a new sequence $E_{1,j}$, $E_{2,j}$,..., $E_{n,j}$. The WT of the i sample under the j indicator is the $WT_{i,j}$ as follows:

$$WT_{i,j} = \sum_{k=1}^{n}\left[S_{k,i} - 100 \times E_{k,j} \Big/ \sum_{l=1}^{n} E_{l,j}\right]^2 \qquad \text{(Equation 12)}$$

$$S_{k,i} = \begin{cases} 100/i, & k \le i \\ 0, & k > i \end{cases} (\, i = 1, 2, ..., n, \quad j = 1, 2, ..., m\,) \qquad \text{(Equation 13)}$$

If the number of main samples under the j indicator is u, it can be calculated as:

$$u = \left(u \middle| WI_{u,j} = \min_i WI_{i,j}\right) \qquad \text{(Equation 14)}$$

Then the main sample set of the j indicator can be obtained as $X_j = (E_{p,j} | p = 1, 2, \ldots, u)$, and the u sample indicator value $E_{u,j}$ is the critical threshold value, and when the sample value of the j indicator is higher than $E_{u,j}$, it is considered an important sample.

The corresponding critical values for each column of the complete consumption matrix and the corresponding critical values for each row of the complete distribution matrix are obtained by comparing the corresponding column and row elements to the critical values, 1 for those above the critical values and 0 for those below the critical values, resulting in backward demand adjacency matrix and forward supply adjacency matrix, and the complex sectoral networks are constructed based on the adjacency matrix, the sectoral relative closeness centrality (including inwards and outwards) and relative intermediary centrality are calculated accordingly. The average clustering, density, reciprocity, and transitivity of the monthly sectoral networks are further calculated to demonstrate the changes in the monthly sectoral network structure captured in the monthly input-output tables, these indicators reflect the degree of connectivity, correlation, level of reciprocal transactions and efficiency of information transmission among the sectors, respectively.

Intersectoral carbon emissions correlation model

Carbon emission analysis is a hot applicate field of input-output tables. We collect sectoral monthly electricity carbon emission data and calculate carbon emission relationships among sectors to reflect their changes in characteristics. The marginal and absolute indicators are established, where marginal indicators reflect the impact of initial inputs and final use on carbon emissions, which can inform decision-making for short-term industrial restructuring. Absolute indicators consider individual industries having higher marginal production or carbon emissions linkages. Still, their overall limited size is less important, so analysis of sectoral carbon emission linkages based on the total amount of initial inputs and final use can assist in long-term sectoral restructuring. Backward correlation marginal indicators can assess a sector's dependence on the supply of raw materials and equipment in other sectors, which is reflected in the column of the Leonsif inverse matrix. The increase in carbon emissions of other sectors driven by the demand increase per unit in sector j is called marginal carbon emission under backward correlation, and expressed as:

$$BLC_j = \sum_{i=1}^{n} e_i l_{i,j} \qquad \text{(Equation 15)}$$

where $l_{i,j}$ is the element in row i and column j of Leonsif inverse matrix, e_i is the carbon intensity of sector i. The marginal carbon emission correlation coefficient under backward correlation (CBLC) of sector j can be calculated as:

$$CBLC_j = \sum_{i=1}^{n} e_i l_{i,j} \Big/ \frac{1}{n} \sum_{j=1}^{n} \sum_{i=1}^{n} e_i l_{i,j} \quad \text{(Equation 16)}$$

If $CBLC_j$ is greater than 1, then impact of unit demand changes in sector j on carbon emissions is higher than the average sectoral level.

Similarly, the Ghosh inverse matrix is used to calculate the forward correlation marginal indicator to reflect the impact of one sector's unit initial input on the total carbon emissions of other sectors, so the marginal carbon emission under forward correlation of sector i can be calculated as:

$$FLC_i = \sum_{j=1}^{n} e_j g_{i,j} \quad \text{(Equation 17)}$$

where $g_{i,j}$ is the element in row i and column j of Ghosh inverse matrix.

The marginal carbon emission correlation coefficient under forward correlation (CFLC) of sector i can be calculated as:

$$CFLC_i = \sum_{j=1}^{n} e_j g_{i,j} \Big/ \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{n} e_j g_{i,j} \quad \text{(Equation 18)}$$

If $CFLC_j$ is greater than 1, then the impact of unit input changes in sector i on carbon emissions is higher than the average sectoral average level.

Absolute indicators assess the intensity of the sectoral carbon correlation based on sectoral production scales, the absolute carbon emission coefficients under backward linkages (BTC) and forward linkages (FTC) are calculated as:

$$BTC_j = \sum_{i=1}^{n} e_i l_{i,j} F_j \Big/ \frac{1}{n} \sum_{j=1}^{n} \sum_{i=1}^{n} e_i l_{i,j} F_j \quad \text{(Equation 19)}$$

$$FTC_i = \sum_{j=1}^{n} e_j g_{i,j} V_i \Big/ \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{n} e_j g_{i,j} V_i \quad \text{(Equation 20)}$$

where F_j is the final use of sector j, V_j is the value added of sector i, BTC_j is the ratio of embodied electricity carbon emission driven by final use of sector j to the average sectoral emission, if it greater than 1, then the emission driven by final use of sector j is higher than average sectoral level. FTC_i is the ratio of embodied electricity carbon emission driven by the initial input of sector j to the average sectoral emission, if it greater than 1, then the emission driven by the initial input of sector j is higher than average sectoral level. A table of variable abbreviations and full names is provided in Table S1.

Data sources and processing

The compilation of monthly input-output tables needs to be supported by published official annual input-output tables, specifically for this study, considering 2018 and 2020 years.[20,21] These tables have a higher priority value than the data collected from the macroeconomic database because they reflect the input-output structure among economic sectors. The sectoral monthly data structure is retained when monthly sectoral data are available. The regulatory coefficient is calculated based on the sum of the monthly sectoral data and the data in the official input-output table to eliminate the scale deviations. For 2019 and 2021, with no official input-output tables, their regulatory coefficients are obtained by linear interpolation. If the monthly sectoral data is missing, the sectoral structure in the official input-output table is considered to be used, the default sectoral data structure is assumed to be the same in each month and is equal to the structure in the official input-output table, and the sectoral structure is also obtained by linear interpolation for 2019 and 2020. Raw data of monthly total output and gross fixed capital formation are obtained from Beijing Tengjing Big Data Application Technology Research Institute. Monthly industrial value added growth rate and quarterly value added were obtained from the National Bureau of Statistics.[22] The household consumption was initially estimated by setting assumptions of unchanged structure combined with an official input-output table. Government consumption was obtained using monthly sub-functional general public budget expenditure data published by the Ministry of Finance.[23] Raw data on monthly imports and exports were obtained from the General Administration of Customs[24] and were adjusted by the US dollar exchange rate for RMB.[25] The raw data collection and processing methods are detailed in the following contents, and we provided the adjusted sectoral value added, total output, and final use dataset in Data S1. There are 39 sectors after data processing, with ID numbers and names in Table S2.

Total output

According to the Beijing Tengjing Big Data Application Technology Research Institute, the sectoral total output is obtained from macro national economic data released by the Bureau of Statistics, industrial enterprises above designated size, service industry, retail sales of consumer goods, fixed assets investment, import and export foreign trade and related price indexes based on the input-output table structure, comprehensively consider the development laws of various industries in the national accounts system from the production side and the demand side, using fill gaps and frequency conversion simulation technology to obtain the monthly total output of each sector.

Value added

The National Bureau of Statistics did not provide monthly industrial value added data, only the monthly growth rate of industrial value added (current and cumulative year-on-year growth rate of industrial value added above designated size) can be obtained. We assume the sectoral monthly value added rate (value added/total output) in 2018 remains unchanged, which is equal to the annual value added rate in the official input-output table. Then, the monthly value added of each sector in 2018 can be obtained based on the monthly sectoral total output, the monthly value added of each sector in 2019, 2020, and 2021 can be further obtained based on the growth rate of sectoral value added.

The year-on-year growth data of value added for January and February is lacking, while the cumulative growth rate provides February data, so the value added in January and February can be obtained through simultaneous equations. The value added in other months are obtained using year-on-year growth rates. The changes in sectoral value added rates between 2018 and 2020 input-output tables are calculated to test the rationality of the unchanged monthly value added rates, the results are shown in Figure S2. Most sectoral value added rates have changed little from 2018 to 2020, with a majority of changes within 5%. The average absolute value of changes in all sectoral value added rates is only 1.72%. Therefore, it is reasonable to assume that the monthly value added rates remain unchanged in 2018. We further assume that the sectoral value added rate in 2019 is the average of 2018 and 2020, and the monthly value added rate also remains unchanged. The priority level of applying this assumption is lower than the application of value added growth rate, that is, if a sector's value added can be obtained through the value added growth rate, this assumption will not be considered. For some sectors that cannot obtain monthly value added through the growth rate (such as the agricultural and service sectors that only publish quarterly value added, and some industrial sectors does not match the sectoral classification from raw data), this assumption is used to calculate sectoral value added to ensure the maximum use of real data.

The sector of "mining auxiliary activities and other mining products" in the total output data are divided into two sub sectors in the value added growth rate data provided by the National Bureau of Statistics as "mining professional and auxiliary activities" and "other mining industries". The difference in the growth rate of value added between the two sub sectors is significant, so its monthly value added is calculated using the value added rate. The primary and tertiary industries lack monthly value added and growth rate data, but the Bureau of Statistics provides quarterly value added and current year-on-year growth rate. Therefore, their monthly value added is calculated using monthly total output and current quarterly year-on-year growth rate. The monthly total output ratio relationship equals to the monthly value added ratio relationship (assuming the monthly value added rate remains unchanged), and the current quarterly year-on-year growth rate is used to determine the quarterly value added. The monthly value added of the primary and tertiary industries in 2018 is calculated directly using the value added rate to ensure consistency with the industrial value added. The value added of primary industry, construction industry, wholesale and retail industry, accommodation and catering industry, transportation, warehousing and postal industry, real estate industry, and financial industry in 2019 and subsequent years are all calculated using a combination of quarterly and current year-on-year growth rates and total output ratios. That is, the quarterly value added is first obtained by using the quarterly and current year-on-year growth rates, and then allocated to the months according to the monthly total output ratio relationship. In the tertiary industry, except for the service sectors that have already calculated their value added, the value added of other service sectors is calculated using the value added rate.

Residential consumption

The raw data of residential consumption only includes monthly consumption data for 11 major categories (food and tobacco, clothing, housing, daily necessities and services, transportation and communication, education, culture and entertainment, medical care, other supplies and services, public healthcare, bank intermediary service consumption, insurance service consumption), which do not match the input-output sectors and are not as detailed as the input-output sectors, This has caused difficulties in data classification (for example, medical care involves both pharmaceutical product consumption and healthcare service consumption). Secondly, even for sectors that are consistently classified, there is still a significant deviation between the collected consumer data and input-output data. For example, the total monthly food, tobacco, and alcohol consumption data collected in 2018 was 8776 billion yuan, while in the input-output table, it was 5587.4 billion yuan (the sum of residents' consumption in the agricultural and sideline food processing and food manufacturing industry, alcoholic beverages and refined tea, and tobacco manufacturing industry). The total amount of clothing consumption data collected in 2018 was 2036.3 billion yuan, while in the input-output table, this item was only 1307.1 billion yuan (the total household consumption value of the textile industry, textile clothing and clothing, leather and feather shoes and clothing sectors). However, the deviation of the total residential consumption data is smaller than the individual sector's residential consumption data. For example, the collected monthly data shows a total consumption value of 35412.4 billion yuan in 2018, which is 34736.3 billion yuan in the input-output table. The total consumption value collected in 2020 is 38718.6 billion yuan, which is 38400.8 billion yuan in the input-output table. Therefore, it is reliable and accurate to use the total consumption to update monthly sectoral residential consumption data. In addition, there was little change in the consumption structure of residents in various sectors in the input-output tables of 2018 and 2020 (the largest change was in other service industries, where the residents' consumption ratio changed from 41.60% in 2018 to 42.64% in 2020, only 1.04% changes). Therefore, it can be assumed that the consumption structure of residents in each month of the year remains unchanged, then the monthly residents' consumption data is updated based on the collected monthly data.

Government consumption

In the input-output tables of 2018 and 2020, only government consumption in 'agriculture, forestry, animal husbandry and fishery', 'transportation, warehousing and postal industry', and 'other service industries' was not zero. Based on this, it can be inferred that in each month of 2018 and 2020, except for the three sectors whose government consumption was not zero, all other sectors were zero. It is further assumed that the same situation will occur in 2019 and 2021. The government consumption of 'agriculture, forestry, animal husbandry, fishery' and 'transportation, warehousing, and postal industry' is determined based on the monthly general public budget expenditure data published by the Ministry of Finance. The monthly functional general public budget expenditure released by the Ministry of Finance lacks cumulative expenditure data for January in each year after 2018. Therefore, assuming that the proportion of data for January and February in each year after 2018 is consistent with that of 2018, the current expenditure data for January and February then can be obtained by combining the cumulative expenditure data for February.

Gross fixed capital formation

The collected data of gross fixed capital formation is also updated by calculating the adjustment coefficient to eliminate the scale effect, where only the 'other manufacturing' sector is missing data, and the gross fixed capital formation of this sector in the input-output table is not zero, but it has the smallest gross fixed capital formation among all sectors. Therefore, it is assumed that its gross fixed capital formation amount is the same in each month of the year to obtain the monthly initial estimate value.

Inventory changes

The National Bureau of Statistics provides monthly inventory data for industrial enterprises, and the missing inventory data for January in each year can be supplemented by the average value of February inventory in that year and December inventory in the previous year. After obtaining the initial value of monthly inventory and comparing it with the total value of inventory changes in the annual input-output table, we found that the data differed greatly, and inventory changes in multiple sectors even showed opposite signs. Specifically, comparing the monthly inventory changes collected with the inventory changes in the 2018 and 2020 input-output tables, the relative range of sectoral inventory changes in 2018 is from 16.8% to 2737.5%, while the range in 2020 is from 15.4% to 1204.8%. Considering that the inventory change data that can be collected does not match well with the inventory change in the input-output table, the collected inventory change data is no longer used, and instead the difference between the estimated total final use value and other final use values is used to calculate the inventory change.

Import and export

The import and export of 'Farming, Forestry, Animal Production and Fishery' are calculated by using the total of the first category (live animals and animal products), the second category (plant products), and the third category (animal vegetable oil and their decomposition products; refined edible oils; animal and vegetable waxes) of the HS code from the General Administration of Customs, this is because the fourth category (food; beverages, alcohol, and vinegar; products of tobacco, tobacco, and tobacco substitutes) and the first three categories effectively distinguish food manufacturing and processing industries from 'Farming, Forestry, Animal Production and Fishery'. The import and export values of mining auxiliary activities and other mining products, gas production and supply industries, water production and supply industries are all 0 in the input-output tables of 2018 and 2020 (the export of gas production and supply industries in 2018 was only 50000 yuan, which can be considered as 0). Therefore, it is assumed that the import and export values of the above sectors in each month from 2018 to 2020 are all 0. The import and export data of the construction industry and other service industries are taken from the international balance of payments service trade data provided by the State Administration of Foreign Exchange, with lenders representing service exports and borrowers representing service imports. The import and export data of the construction industry is taken as the 'construction difference' category data, the wholesale, retail, accommodation, and catering industry is taken as the 'travel difference' category data, the transportation, warehousing, and postal industry is taken as the 'transportation difference' category data, and other service industries are taken as the 'service trade difference' after deducting the above three items. The above data all collected in US dollar units. After collection, the original data is adjusted to be in Chinese yuan using the monthly average exchange rate published by the State Administration of Foreign Exchange.

Intermediate use

The intermediate use of sectors is an important variable in updating the input-output table. Figure S3 shows the sectoral intermediate use structure in the official input-output table for 2018 and 2020. It can be seen that the change in the intermediate use structure is very small, with sector 39 having the largest structural change increased from 0.190 in 2018 to 0.209 in 2020, with only a change of 0.019. Therefore, it can be assumed that the intermediate use structure of each month for four years is the same as its annual intermediate usage structure, and the intermediate use structures for 2019 and 2021 are obtained through linear interpolation method. According to the balance relationship between the total values of the second and third quadrants of the input-output table, combined with the monthly total output and monthly value added, the monthly intermediate use can be obtained. Combined with the monthly intermediate use structure, the sectoral monthly intermediate use value can be obtained. The monthly final use value is further obtained by subtracting the monthly intermediate use value from the monthly total output value.

For electricity emissions data, the monthly current and cumulative electricity consumptions of primary, secondary, industrial, and tertiary industries are obtained from the National Energy Agency.[26] Based on the monthly electricity consumption of the primary, secondary, industrial, and tertiary industries, as well as the product distribution coefficient of S33-Production and Supply of Electricity and Steam in the intermediate consumption matrix of each month's input-output tables, the proportion of electricity consumption in each sector is determined to obtain sectoral electricity consumptions. The monthly electricity consumption of the construction industry is obtained by the difference between the secondary industry and the industry (the secondary industry consists of the industry and the construction industry, while the industry includes manufacturing, mining, electricity and steam, gas and water production and supply industries). The monthly electricity consumption of the primary industry corresponds to S1-Farming, Forestry, Animal Production, and Fishery. S2-S35 belongs to industry, while S37-S39 are tertiary. Carbon emission factors for electricity energy are obtained from the Ministry of Ecology and Environment.[27] The national grid emission factors were 0.6101 tCO_2/Mwh in 2015 and 0.5810 tCO_2/Mwh in 2021, so the emission factors are shown in Table S3 with a linear difference for the intermediate years. We further used the monthly consumer price index to adjust the input-output table data for different months to the price level of January 2018, in order to eliminate the impact of price fluctuations on the results.