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Constructing Time-Series Input-Output Systems and Exploring Carbon Development Measures: From Retrospect to Prospect

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Abstract

Input-output table (IOT) and social accounting matrix (SAM) are two interconnected but unique input-output systems in the area of economy. Constructing time-series input-output tables (IOTs) and social accounting matrices (SAMs) fulfils two tipping points. One is concerned with tracing the structural trajectories of economic systems from the past to the future. The other is with regard to rendering economic systems analytical dynamically and effectuating the explorations of various external variables from the time dimension. Further, environmentally extending time-series IOTs and SAMs with newly proposed techniques could be considered as meaningful feedbacks for the development of time-series input-output systems.

Favourable endeavours have been devoted to constructing time-series IOTs and SAMs, and, correspondingly, to exploring carbon development measures. However, increasing attention could be drawn to the role of utilizing and exploiting the fundamental and important features of input-output systems in achieving the aforementioned objectives. This consideration promotes the methods improvements of the five chapters (Chapters 2 to 6) of this thesis.

(1) Updating time-series input-output tables with economic structure concerns and identifying CO_2 clusters changes. Time-series input-output tables (IOTs) elaborate economic structures over time. In this study, we therefore utilize economic structure concerns to update time-series IOTs. A new matrix calculation method is proposed for tracking and establishing matrix-based links among intermediate input-outputs, final demand and value added. The method is reinforced by reflecting price fluctuations in IOTs. This method is further extended by proposing a matrix-based linking method to trace the structure changes of final demand and value added. The validation analysis of time-series IOTs is conducted using Monte Carlo simulations in the context of the matrix-based structures of IOTs. Based on the time-series IOTs, CO_2

clusters changes from production, consumption and income perspectives are identified, deriving sector characteristics to reduce CO_2 emissions. This study is in the case of China from 1997 to 2020.

(2) <u>A forward-backward realization of solutions to time-series social accounting matrices construction, validation and applications.</u> Social accounting matrix (SAM) elucidates the economic transactions flowing forward and backward, thereby forming a matrix-based structure. This feature is exploited, constituting a forward-backward realization of solutions to time-series SAMs construction, validation and applications. In this study, the matrix-induced structure features time-series SAMs construction, during which K-nearest-neighbour algorithm and leave-one-out cross-validation are joint to handle missing data. Also, a new matrix calculation method is proposed to conduct time-series SAMs validation in terms of gauging the economy-wide effects of each economic agent. Using time-series SAMs, both demand- and supply-driven CO_2 emissions are analysed and compared by extending multiplier decomposition analysis and structural path analysis. This study is in the case of China from 1997 to 2020.

(3) <u>Input-output forecasting and CO_2 inventories construction using a new subsystem decomposition analysis.</u> Forecasting input-output tables and social accounting matrices is an attempt to trace the trends inherent in the economic system, and to render the economic system analytical when exploring the future of various external variables. In this study, we therefore propose a procedure of input-output forecasting. During this procedure, the input-output table series are forecasted by proposing an element-based Fourier-Markov method, then structured through modified matrix transformation technique and T-accounts concept, and last, validated by combining matrix calculation methods with Monte Carlo simulations. On the basis of the forecasted table series, we construct CO_2 inventories by proposing a new integrated method, that is, the combination of subsystem analysis with structural decomposition analysis. With this method, CO_2 inventories quantify historical and future emission channels throughout the economic system from demand and supply sides, and then account for the contributions of influencing factors behind temporal changes in emission channels. This study is in the case of China from 1997 to 2025.

(4) An integrated scheme of input-output future scenarios construction interconnecting production with consumption and sector-level CO_2 emissions synergistic alleviation. In response to the explorations of prospective trajectories, input-output analysis (IOA) in a scenario context could encompass intra- and inter-sector linkages in future scenarios, and also investigate the potential pathways of external variables. When integrating IOA and scenario analysis, multi-criteria decision making techniques have found to be feasible and useful. Against this backdrop, we propose an integrated scheme of input-output future scenarios construction to help alleviate CO_2 emissions in a holistic manner. That is, we set up three categories of input-output future scenarios by interconnecting production with consumption. In detail, we start input-output BAU scenario through a procedure of input-output forecasting. We then construct input-output policy-related scenario by extending the multi-objective optimization method with multiple policy-related parameters. We finally arrange input-output problem-specific scenarios using multi-attribute decision making which incorporates the generalized weighting method into the permutation and combination method, and supports the construction of a multi-attribute importance method. Within the three constructed categories of input-output future scenarios, sector-level CO_2 emissions synergistic alleviation is analysed. This study is in the case of China from 2020 to 2030.

(5) Input-output future configuring system for low-carbon economy using a social accounting matrix optimization design. To reflect and reconcile the future trends in the context of low-carbon economy (LCE), this study proposes an input-output future configuring system for LCE. This system is constructed by a social accounting matrix optimization design, which is achieved within the computable general equilibrium

(CGE)-based framework. During the system construction, optimum designs are conducted for LCE performance and planning-based parameter setting. Then, a CGE appraisal framework is integrated into optimization. Also, this system is validated through Monte Carlo simulations. When applying this system to the LCE context, a new method is proposed through combining the element-based Fourier-Markov method with the simultaneous equations method, so as to analyze the impacts of future trends on economy, energy and CO_2 emissions are analyzed and suggest countermeasures correspondingly. This study is in the case of China from 2020 to 2030.

Contents

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Chapter 1: Introduction

1.1. Research background

Input-output table (IOT) and social accounting matrix (SAM) are two interconnected but unique input-output systems in the area of economy (Leontief, 1970, 1975; Gretton, 2013; Thorbecke, 2000; Barnard, 1969). An IOT is an activity-based input-output table illustrating the flows of goods and services among different sectors (Leontief, 1974). In an IOT, each row shows the allocation of a certain sector production to the intermediate consumption of other sectors and to final demand and each column presents the value structure of the output of a certain sector (Keček et al., 2022). A SAM is a double accounting economic matrix whereby each economic account is represented by a column for expenditures and a row for incomes (Pal and Bandarlage, 2017), reconciling all economic transactions between agents such as industrial activities, institutions, and factors (Hartono and Resosudarmo, 2008), and forming a circle of income distribution and spending (Campoy-Muñoz et al., 2017). Further, because the production activities of SAM are consistent with the structure of IOT, SAM classifies not only the entire economic circulation but also the detailed structure of production activities by incorporating IOT (Ge and Lei, 2013; Itoh, 2016).

Therefore, an IOT elaborates the economic structure by delineating intra- and inter-sector linkages affected by final use and value added (Leontief, 1986; Miller and Blair, 2009). It is constructive in a broad manner in terms of reflecting how the economy operates (Jensen et al., 1988) and reconciling the trade-offs related to the economy (Oliveira et al., 2016). A SAM captures the entire circular flows of income with the connections of economic activities among economic agents (Defourny and Thorbecke, 1984). It is extensively practical in gauging the impacts of demand and supply (Fernández-Macho et al., 2008) and in building up models for structural and policy analyses (Blancas, 2006).

Against this backdrop, constructing time-series input-output tables (IOTs) and social accounting matrices (SAMs) from retrospect to prospect facilitates tracing the structural trajectories of the economic system from the past to the future, which further renders the economic systems analytical dynamically and effectuates the explorations of various external variables such as CO_2 emissions from the time dimension.

1.1.1. Constructing time-series IOTs and SAMs from retrospect to prospect

From a retrospect perspective, constructing time-series IOTs and SAMs helps comprehend economic systems over time. To illustrate, time-series IOTs elaborate the structures of economy across time. In detail, they reflect the continuous sectoral interconnections within an economy (Harry and Keiko, 2015), are used as the long-term reference data for economy-related phenomena (Timmer et al., 2012), and provide data supports for econometric modelling (Hübler et al., 2022), social accounting matrix (Cho and Díaz, 2019), computable general equilibrium model (Hübler and Pothen, 2017), integrated assessment model (Capellán-Pérez et al., 2020), and other models (Lombardi et al., 2019).

Meaningful studies have been conducted using time-series SAMs. For example, analyzing the socio-economic situation of an economy in a historical manner is carried out (Bakker et al., 1994); unveiling the sectoral impacts directly and indirectly over time is achieved (Akkemik, 2012); statistically estimating parameters that characterize the people in artificial economy is conducted (Kehoe, 1996); supporting structural change analysis and back-casting/calibration of computable general equilibrium models is accessible (Seventer, 2015); and serving as grounded empirical evidence to contribute to the development of (socio)economic theory is achievable (Santos, 2006), and forecasting the long-run trends of the system structure is fulfilled (Hartono and Resosudarmo, 2008).

From a prospect perspective, constructing time-series IOTs and SAMs helps explore the future development of economic systems. In detail, the input-output systems are formulated to reflect the timeliness of input-output systems which has been emphasized in terms of long time lag of the released table series (Dietzenbacher et al., 2013; Wang et al., 2015b). For example, these table series are very often released every five or more years (Dietzenbacher et al., 2013; Wang et al., 2017). Also, the input-output systems contribute to manifesting the long-run trends of the economic system structure (Hartono and Resosudarmo, 2008), which is particular the case when trends importantly characterize the development of variables (Michieka et al., 2013; Wang et al., 2015a; L.-Y. Zhang et al., 2019). Then, the input-output systems could be attainable and useful in response to the investigations in terms of strategic planning and anticipation on future development (Sharify and Batey, 2006; Faber et al., 2007; Mi et al., 2015). Besides, the input-output systems could be configured and flexible in reflecting and reconciling the future trends of economy, especially when interdisciplinary viewpoints are considered in economic development (Mi et al., 2017c; S.-W. Yu et al., 2018b; Y.-Q. Su et al., 2021).

1.1.2. Extending time-series IOTs and SAMs from retrospect to prospect

Time-series IOTs and SAMs provide systematic viewpoints for their extensions to various external variables. From a retrospect viewpoint, time-series IOTs are of importance in many contexts, such as exploring energy consumption (Meng et al., 2020), investigating greenhouse gas emissions (Wiedmann et al., 2010), measuring environmental sustainability performance (Acquaye et al., 2017), and assessing sustainability impacts (Egilmez et al., 2020). Also, on the basis of time-series SAMs, diverse studies could be conducted. To illustrate, the effects of exogenous changes in injections and transfers on output growth and income distribution are captured (Cohen, 1989), the economic significance of tourism activity in the economy is estimated (West, 1993), the trade-offs between ecological and socio-economic systems are quantified (Y. Wang et al., 2016), and the principal paths through which financial shocks are transmitted are identified (Aray et al., 2017).

From a prospective viewpoint, time-series IOTs and SAMs have provided analytical frameworks for conducting forecasts and simulations, so as to investigate the future development of external variables in various fields such as environment, energy, demography, resources, and management. Specifically, the multi-step forecasting procedure for carbon emissions embodied in bilateral trade is proposed on the basis of cleaner production level and industrial structure (S. Wang et al., 2019). The model for energy requirements and CO_2 emissions in the future is established based on the input-output (IO) model (Fan et al., 2007). The urban land-use demand is forecasted using a metropolitan IO model (Jun, 2005). The IO model for management control and financial planning is feasible in the phase of simulation and planning (Marangoni and Fezzi, 2002). The functioning of the economy under differentiated demographic structures is investigated using the SAM framework (Cohen and Tuyl, 1991). The integrated land-use and transport modelling framework using SAM is applicable in situations where there is a need for consistent land-use and transport predications and evaluations (Hunt and Simmonds, 1993). The SAM framework is useful for predicting the impacts of an improvement in energy efficiency and a restriction on energy use (Hartono and Resosudarmo, 2008).

1.1.3. Exploring carbon development measures from retrospect to prospect

As one of the extensions of time-series IOTs and SAMs, time-series CO_2 emissions have been increasingly explored. Further research in this area should be encouraged given more recent useful research on time-series CO_2 emissions. From a retrospective angle, the explorations of time-series CO_2 emissions help (1) understand the trend of CO_2 emissions (Lim et al., 2009; Zhang et al., 2009; Cai et al., 2020; Hou et al., 2020), (2) analyse the influencing factors behind the related temporal changes of CO_2 emissions (Zhang et al., 2009; Xu and Lin, 2016; Dong et al., 2020), (3) meet the requirements of achieving the control of total CO_2 emissions and emissions intensity (Yi et al., 2016; Cai et al., 2020), (4) formulate CO_2 emissions reduction measures (J.-

S. Li et al., 2016; Xu and Lin, 2016; Yi et al., 2016; Cai et al., 2020), and (5) provide the historical data for future studies (Yi et al., 2016).

Then, from a prospective angle, the explorations of time-series CO_2 emissions help (1) understand the future situation of CO_2 emissions abatement (J.-B. Huang et al., 2019; Lin and Wang, 2021), (2) analyse the potential for CO_2 emissions reduction (Wang et al., 2007; Lin and Tan, 2017), (3) attain total CO_2 emissions and CO_2 emissions intensity targets (Yi et al., 2016; D. Wang et al., 2019), (4) formulate the CO_2 emissions reduction measures through identifying potential determinants in the future (Yi et al., 2016; D. Wang et al., 2019; L.-Y. Zhang et al., 2019); (5) provide a complementary comparison with retrospective results (J. Wang et al., 2019), and (6) extend the methodological innovations into other fields, such as economy (Dong et al., 2018), energy (Lin and Tan, 2017), and environment (Dong et al., 2015).

1.1.4. Constructing time-series input-output systems and exploring carbon development measures in the case of China

In China, updating time-series input-output systems including IOTs and SAMs is necessary and meaningful, which concentrates on the merits of time-series systems discussed in Sections 1.1.1 to 1.1.3. Official IOTs are with time intervals in China (Wang et al., 2017): benchmark IOTs (i.e., IOTs based on survey method) depict economy-wide sectoral linkages in the years whose last digits are 2 and 7, followed by extended IOTs (i.e., IOTs based on non-survey methods) every two years. Then, there are not available official SAMs published and the construction of time-series SAMs is also needed (Wang and Li, 2008).

Meanwhile, applying time-series input-output systems to the field of CO_2 emissions is closely connected with combating climate change in China. As a developing country with greatest carbon emissions per annum, China has been actively participating in the alleviation of the global greenhouse gas effect (Zheng et al., 2016; Yu et al., 2022). The

Chinese government promised at the Copenhagen Climate conference in 2009 that by 2020, China's carbon emission intensity would be reduced by 40-45% compared with 2005. In 2016, in the Paris Agreement, the Chinese government committed to reducing carbon emissions intensity by 60-65% by 2030 compared with 2005. In 2020, the Chinese government demonstrated the commitment at the UN General Assembly that China will increase its national independent contribution, adopt more effective policies and measures, and strive to peak CO_2 emissions by 2030 and achieve carbon neutrality by 2060. Against this backdrop, the time-series input-output methods have been applied to investigate the roles of sectoral linkages, acting paths and influencing factors in the process of CO_2 emissions reduction (Chen and Zhang, 2010; Wang et al., 2013; Yang et al., 2015a), to cast diverse insights into the significance of supply and demand sides to CO_2 emissions alleviation (Zhang, 2010; L.-C. Liu et al., 2016; Zhao et al., 2017), to set up multiple scenarios for assessing and managing the decrements in CO_2 emissions (Mi et al., 2017c; Fang et al., 2019; Y. Su et al., 2021), and thus to propose targeted and operable suggestions for carbon abatement strategies (L. Li et al., 2016; Mi et al., 2018a; X.-R. Lin et al., 2020). In these regards, investigating the carbon development measures by means of input-output systems manifests the exploratory importance.

1.2. Related research

Related research is conducted to tackle problems in constructing time-series input-output systems from retrospect to prospect, and correspondingly, exploring carbon development measures. Previous researches include (1) constructing time-series IOTs from a retrospect perspective; (2) constructing time-series SAMs from a retrospect perspective; (3) constructing time-series IOTs and SAMs from a prospect perspective; and (4) exploring carbon development measures from retrospect to prospect.

1.2.1. Constructing time-series IOTs from a retrospect perspective

Many endeavours have been made to construct time-series IOTs. RAS (one bi-proportional matrix balancing technique) balances positive IOTs on the basis of sector-level gross outputs, and intermediate input-outputs (Ahmad, 2002; Miller and Blair, 2009; Timmer et al., 2012; Harry and Keiko, 2015). RAS extensions tackle negative IOTs and inconsistent constraints, such as GRAS (Tukker et al., 2013; Wood et al., 2014) and KRAS (Lenzen et al., 2009). The Leontief dynamic IO model improves static IO models by exploring intertemporal and inter-sectoral relations between capital change and technological levels (Leontief, 1986). For example, the Leontief IO model is extended by introducing new capital and labour matrices to explore impacts of technological progress (1997-2100) (Pan, 2006), and by introducing human capital to study dynamic relations between the education sector and other sectors (2000-2010) (Zhang and Chen, 2008). The dynamic IO model is established to closely fit specific questions, without enough focus on relaxing constraints from dynamic links between capital and technology (Leontief, 1986). Matrix transformation technique (MTT) has been applied recently (Wang et al., 2015a; Zheng et al., 2018). Through a matrix calculation method, MTT tracks distributional impacts of sectoral value-added on intermediate economic transactions and final demand, forming a matrix-based structure. Also, MTT emphasizes economic structure changes over time, rather than the assumption that technological coefficients are stable in the time dimension.

Yet, the process of constructing time-series IOTs still needs some economic structure concerns. First, despite the novelty of MTT, the weaknesses of MTT arise when (1) final demand signs are inconsistent between two IOTs to use, (2) nonlinear interpolation is considered to reflect temporal changes, and (3) there is a need to depict the propagation relationship between Ghosh model and the IOT-related models. To reconcile this, a new matrix calculation method is needed. Second, as structural transformation is measured at constant prices (Herrendorf et al., 2014), price fluctuations in IOTs need to be reflected. Because the proposed new matrix calculation method establishes the matrix-based links among intermediate input-outputs, final demand and value added, price indices are applied directly in the matrix-based links when the matrix-based structure is preserved. Last, to trace the structure changes of final demand and value added, the exact temporal impacts of each element of final demand and value added need to be captured, and linked with intermediate input-outputs. The existing methods for updating the categories of final demand and value added are primarily for balancing the initial estimate at the aggregate level and do not emphasize economic structure changes (Huang et al., 2008; Wang et al., 2015a). Hence, a new matrix-based linking method is needed. The characteristics of this new method include achieving automatic and straightforward adjustments when capturing and linking structure changes, and reflecting linear and/or non-linear impacts over time.

The validation analysis of IOTs is conducted from various angles. In detail, matrix similarity indicators are applied to investigate the similarities among different versions of IOTs (Steen-Olsen et al., 2016). Statistical indicators for error estimation are utilized to understand the differences between estimated IOTs and referenced IOTs (Wang et al., 2015a). The Sherman-Morrison-Woodbury formula is applied in the sensitivity analysis by providing the impacts of each direct consumption coefficient (Wilting, 2012a). The matrix perturbation analysis is modified to study how environmentally extended IO model is sensitive to the changes of parameters (Mattila et al., 2013). Monte Carlo simulations are applied to the Leontief model to explore uncertainties of IOTs (Wilting, 2012a), which provide more statistical information about the results. Correspondingly, with the aim of depicting the direct and deterministic effects of variables to explore in the IOT framework (Zheng et al., 2018), Monte Carlo simulations could be utilized in the context of the matrix-based structures of IOTs.

1.2.2. Constructing time-series SAMs from a retrospect perspective

SAM could be constructed in a top-down or bottom-up manner. In the former, micro SAM is detailed on the basis of macro SAM (Stuttard and Frogner, 2003), whilst in the latter, data reconciliation methods (e.g., naïve method, RAS, and cross entropy) are utilized (Robinson et al., 2001; J. Round, 2003; Temurshoev et al., 2013; Scandizzo and Ferrarese, 2015). Despite the discrepancies between the two manners, there exists a common and illuminating sense, that is, both the coherent relationship between IOT and SAM as well as the potential contributions of T-accounts concept to SAM are of significance during the construction (Pyatt, 1999; J. Round, 2003; J. I. Round, 2003; Lemelin et al., 2013). Following this sense, more details are exploited. IOT is the representation of the economic structure embedded in production activities. Based on IOT, SAM develops into a general equilibrium data system linking economic activities among economic agents (including endogenous and exogenous economic accounts). These two concerns highlight the importance of considering that IOT is not only the main and consistent component of SAM, but IOT itself also needs a detailed construction reflecting its economic structure. Then, when considering the T-accounts, they show the balance between demand and supply for each good or service over a specific accounting period (Pyatt, 1999), and are used to achieve the fundamental characteristic of a double entry accounting system (Ellerman, 1986). Meanwhile, SAM is a double-entry bookkeeping table (Blancas, 2006) which describes an accounting system unravelling the inter-sectoral connections in such a way that, for each account, total income and total expenditure must be the same (Fernández-Macho et al., 2008). This similarity supports the determination of economic accounts included in SAM and the balance of the whole SAM.

In these regards, to construct time-series SAMs, keeping the consistency between time-series IOTs and time-series SAMs, and integrating T-accounts into time-series SAMs are simultaneously important. Regarding time-series IOTs construction, the modified MTT (MMTT) method is used. The features of the MMTT method include: (1) probing into and then establishing a matrix-based economic structure (i.e., matrix-based links among intermediate input-outputs, final demand and value-added); (2) emphasizing changes in economic structure over time; (3) adding up in the situation where the final demand signs are inconsistent between the prior table and the target table; (4) making sense regardless of whether the data assumptions are linear or nonlinear; (5) depicting the propagation relationship between Ghosh model and the IOT-related models; and (6) tracing structure changes of final demand and value added through the matrix-based linking method. Then, with time-series IOTs, T-accounts concept is applied to establish the accounts included in time-series SAMs, and is also utilized to reconcile time-series IOTs with the established accounts.

Meanwhile, it is also noted that missing data is a phenomenon occurring during time-series SAM construction. Among the methods of handling missing data, K-nearest-neighbour (KNN) algorithm is characterized by straightforward concept, convenient implementation, no requirement for prior knowledge about data distribution, no assumptions on data and missing data mechanisms, and efficient learning from small samples (S.-Y. Liang et al., 2015; Idri et al., 2016; Wang and Wang, 2019; Liao et al., 2020). These characteristics are well-suited to missing data estimation in the context of time-series data. Regarding the influence of the parameter (i.e., the number of selected neighbours) on the KNN algorithm performance, left-one-out cross-validation (LOOCV) is applied to determine the number of neighbours chosen. The advantages of LOOCV include that (1) it is a deterministic procedure (Kocaguneli et al., 2012); (2) it can be sure that the optimum value derived from this method is the absolute optimum value, rather than the local optimum values (Modaresi et al., 2018); and (3) it is an effective validation method for KNN algorithm in the context of small samples (Molinaro et al., 2005; Farahnakian et al., 2013).

There are two constructive ways for SAM validation. One method is useful in exploring the impacts of the row totals and the column totals on a SAM structure (Robinson et al., 2001). But the impacts of each element on one SAM are therefore unavailable during this process. The other approach is supportive in introducing the stochastic changes of variables to the validation procedure. But the starting point is from the formalized problem of constrained maximization within the context of generalized cross entropy model (Scandizzo and Ferrarese, 2015; Wang et al., 2015a). Thus, how to reflect the effects of each component on the matrix-based SAM structure could be a consideration in need of attention. It could be noted that, in spite of the differences between IOT and SAM, there also exist similarities between them (Bakker et al., 1994). In detail, the essence of IOT is that industries are connected through the buying and selling of raw materials and that the production structure is conditioned by linkages (Pyatt, 1999). By the same taken, the essence of SAM is concerned with the matrix of transactions and transfers between different institutions (Pyatt, 1999). In this respect, MTT is not constrained to an avenue towards updating time-series IOTs (Wang et al., 2015a) since MTT probes into the economic structure by tracing and establishing matrix-based links, but is considered as a basis to validate SAMs by detecting the matrix-based links within a square matrix.

1.2.3. Constructing time-series IOTs and SAMs from a prospect perspective

1.2.3.1. Input-output forecasting

Studies about input-output forecasting could be classified into two categories. One is concerned with forecasting some external variables (or conducting simulations) by using the benchmark input-output table series as model inputs (Marangoni and Fezzi, 2002; Jun, 2005; Fan et al., 2007; Yu et al., 2016b; S. Wang et al., 2019). The other is about forecasting IOTs through econometric method (Zheng et al., 2017), or scenario-based method (Beaufils and Wenz, 2022). During the procedure of input-output forecasting, three aspects are of significance, including: (1) how to forecast the input-output systems; (2) how to structure the forecasted trends of variables within the input-output systems; and (3) how to validate the forecasted input-output systems.

To forecast the input-output systems, related studies use RAS method or autoregressive integrated moving average (ARIMA) method. The RAS method is used primarily for balancing an initial estimate (Wang et al., 2015b), and further, when RAS is combined with macroeconomic data assumptions, the results to obtain are affected by stochastic uncertainties (Jiang et al., 2019a). The ARIMA model depends on a large amount of data (Wang, 2013), and also requires the mean and variance of response series are independent of time (Y.-W. Wang et al., 2018).

Besides the above-mentioned methods, there are many approaches to predicting external variables (Li et al., 2007; Feng et al., 2012; Zeng et al., 2018), such as regression analysis, time series analysis, grey model, and nonlinear intelligent models. However, regression analysis is limited if there are insufficient data, or if the data are sufficient but not follow certain distribution patterns (Ho, 2010; Belayneh and Adamowski, 2012). Time series analysis requires a large amount of data for forecasting and assumes a linear relationship between the dependent and independent variables while the actual data often present nonlinear relationships (Zhang, 2003; Y.-W. Wang et al., 2018). Grey model could not generate satisfactory predictions when data are nonlinear and has worse curving fitting effects in case of random data (Hsu et al., 2009; R. Wang et al., 2018; Y.-S. Wang et al., 2018). Nonlinear intelligent models depend on a large amount of data; and also these methods need the representativeness of data sets and model interpretability (Pao et al., 2012; J.-D. Wang et al., 2018; Zhao et al., 2022).

The Fourier-Markov model is a mathematical technique for predicting the future values of a time series when the difference between the forecasts from basic models and initial estimates is taken into consideration (Lin et al., 2001; Su et al., 2002). This method has been conceived as a way of enhancing the accuracy of forecasting (Hsu et al., 2009). However, the previous Fourier-Markov method cannot guarantee the accuracy of each observation, cannot ensure the constant good performance when compared with its original model that is based on, and will decrease the scope of application as its current form is not specified in a broad manner. To address these weaknesses, we propose an element-based Fourier-Markov (EFM) method. Also, the EFM method could be applied regardless of whether the amount of data is large or not, which retains the advantages of the Fourier-Markov method (Lin et al., 2001; Su et al., 2002; Hsu et al., 2009).

Besides, the EFM method could be used in the context of short- and long-term forecasting because the conversion matrix in the Markov process and the input parameters of the basic module of Fourier-Markov method could be adjusted according to the changes in future trends (Alfieri et al., 2015; Z. Zhang et al., 2021; Rahnama, 2021). Taking land use as an example, to analyse the future changes of wetlands under the future scenario which is centred on economic construction, the conversion elasticity coefficient of non-wetland increased, and the elasticity coefficients of other wetland types remain unchanged. Correspondingly, the Markov transfer matrix is adjusted, the conversion rate of each wetland type to non-wetland is set to increase by 50%, and the mutual conversion rate of other wetland types is not changed (Z. Zhang et al., 2021). For another example, the basic module of the Fourier-Markov method could proceed with adaptive forecasting that suits the requirements of different planning and future development strategies, which casts its capability of tracking both linear and nonlinear changes in time series data, and its flexibility of directing the future trends when temporal changes occur in practice by means of its model construct (Alfieri et al., 2015).

The ways of structuring the forecasts differ, depending on the type of the input-output system. In detail, in the context of IOTs, some studies use RAS method to structure the forecasts (Beaufils and Wenz, 2022), and other studies use MTT method to accomplish the structuring (Zheng et al., 2017). The estimates on the basis of RAS method is the outcome of input-output forecasts structuring, but, as mentioned before, RAS is used primarily for balancing an initial estimate. The weaknesses of MTT arise when (1) final demand signs are inconsistent between the prior table and the target table, (2) nonlinear interpolations are considered to reflect temporal changes, and (3) there is a need for depicting the propagation relationship between Ghosh model and the IOT-related models. Except for these concerns, the studies above do not consider the unfolding of final demand and value-added to demonstrate the corresponding categories. In detail, to trace the structure changes of final demand and value added, the exact temporal impacts of each element of final demand and value added need to be captured, and linked with intermediate input-outputs. The existing methods for updating the categories of final demand and value added are primarily for balancing the initial estimate at the aggregate level and do not emphasize economic structure changes (Huang et al., 2008; Wang et al., 2015a). Hence, a new matrix-based linking method is needed. The characteristics of this new method include achieving automatic and straightforward adjustments when capturing and linking structure changes, and reflecting linear and/or non-linear impacts over time.

In these regards, the MMTT method realizes the following contents, including (1) probing into and then establishing a matrix-based economic structure (i.e., matrix-based links among intermediate input-outputs, final demand and value-added); (2) emphasizing economic structure changes over time; (3) adding up in the situation where the final demand signs are inconsistent between the prior table and the target table; (4) making sense regardless of whether the data assumptions are linear or nonlinear; (5) depicting the propagation relationship between Ghosh model and the IOT-related models; and (6) tracing structure changes of final demand and value added through the matrix-based linking method.

When turning to the context of SAMs, current studies do not concentrate on the structuring of input-output forecasts. But the relationships among IOTs, SAMs and T-accounts concept could be supportive in addressing the issue above. Based on IOT, SAM develops into a general equilibrium data system linking economic activities among economic agents (including endogenous and exogenous economic accounts). Then, T-accounts show the balance between demand and supply for each good or service over a specific accounting period (Pyatt, 1999), and are used to achieve the fundamental characteristic of a double entry account system (Ellerman, 1986). In the meantime, SAM is a double-entry bookkeeping table (Blancas, 2006) where it describes an accounting system unravelling the inter-sector connections in such a way that, for each account, total income and total expenditure must be the same (Fernández-Macho et al., 2008). In these regards, MMTT in combination with T-accounts concept could be utilized to complete the structuring of SAMs forecasts.

Although current studies do not take into consideration the validation of input-output forecasts, the techniques for validating updated IOTs and SAMs have been proposed. In the context of IOTs, matrix similarity indicators are applied to investigate the similarities among IOTs of different versions (Steen-Olsen et al., 2016). Statistical indicators for error estimation are utilized to understand the differences between estimated IOTs and referenced IOTs (Wang et al., 2015b). The Sherman-Morrison-Woodbury formula is applied for sensitivity analysis by studying the impacts of each direct consumption coefficient (Wilting, 2012a). The matrix perturbation analysis is modified to explore how environmentally extended input-output model is sensitive to the changes of parameters (Mattila et al., 2013). Monte Carlo simulations are applied to Leontief model to investigate uncertainties of IOTs (Wilting, 2012a), which provide more statistical information in relation to the results.

Then, in the context of SAMs, one method explores the impacts of the row totals and the column totals on a SAM structure (Robinson et al., 2001). But the impacts of each element on one SAM are therefore unavailable during this process. The other approach introduces the stochastic changes of variables to the validation procedure. But the starting point is from the formalized problem of constrained maximization within the context of generalized cross entropy model (Scandizzo and Ferrarese, 2015).

In these respects, how to reflect the effects of each element on the matrix-based IOT (or SAM) structure could be a consideration in need of attention. The MMTT method, as mentioned before, probes into and then establishes the matrix-based IOT structure, forming the matrix-based links among intermediate input-outputs, final demand and value-added. Then, on the basis of the properties of a SAM and the characteristics of the MMTT method, a matrix calculation method could be proposed to investigate and then establish the matrix-based SAM structure. Further, with Monte Carlo simulations, these established matrix-based structures could be used to validate the forecasts of the input-output systems.

1.2.3.2. Input-output future scenarios construction

During the procedure of integrating input-output analysis (IOA) and scenario analysis, multi-criteria decision making (MCDM) has been found to be feasible and useful. This is because not only does MCDM suit the real world problems involving multiple, conflicting and incommensurable objectives (Oliveira and Antunes, 2004; San Cristóbal, 2012; Oliveira et al., 2016), but this technique also provides an approach towards the trade-offs among multiple attributes and multiple objectives (Weng et al., 2010; De Carvalho et al., 2016; Abdullah et al., 2021). For example, multi-attribute decision making methods (i.e., the first category of MCDM) are used to allocate CO_2 emissions among sectors by considering the impacts of various attributes in terms of capacity, responsibility, and potential (Zhao et al., 2017). For another example, multi-objective optimization methods (i.e., the second category of MCDM) are used to investigate whether energy savings goal is achieved when the decision-making process is confronted with multiple objectives in terms of economy, energy and environment (S.-W. Yu et al., 2018b).

Within the input-output future scenarios, ‘business-as-usual’ (BAU) scenario is set as a reference to explore the impacts of influencing factors on external variables (Faber et al., 2007; X. Zhang et al., 2017; Ma et al., 2020), and thus subsequent scenario settings are formulated by incorporating specific elements (e.g., multiple objectives, multiple criteria) into the reference scenario (Chen et al., 2014; Oliveira et al., 2016; Ma et al., 2020). However, during the construction of input-output future scenarios, the interconnections between production and consumption have not been emphasized, despite that these interconnections fundamentally characterize the IOA scheme and related extensions to environment (Oliveira and Antunes, 2004; Weng et al., 2010; Carvalho et al., 2015; Oliveira et al., 2016; Rojas Sánchez et al., 2019).

To construct input-output future scenarios through the interconnections between production and consumption, some concerns need to be coped with, which include (1) how to start BAU scenario by considering the temporal changes of economic system depicted by input-output tables; (2) how to construct policy-related scenario by extending the multi-objective optimization method with multiple policy-related parameters for the trade-offs among multiple objectives; and (3) how to arrange problem-specific scenarios when traversing all the potential decision preferences among multiple attributes, and constructing a multi-attribute importance method to allocate importance among sectors are needed and feasible.

Regarding the construction of BAU scenario, RAS method is used to reflect the temporal changes of economic system depicted by input-output tables (Yu et al., 2016b; S.-W. Yu et al., 2018b). Despite the usefulness and efficiency, RAS method is mainly used for balancing the initial table (Wang et al., 2015a). Then, matrix transformation technique (MTT) is a method emphasizing economic structure changes over time by investigating a matrix-based economic structure (i.e., matrix-based links among intermediate input-outputs, final demand and value added) (Wang et al., 2015a). However, the weaknesses of MTT arise when (1) final demand signs are inconsistent between the prior table and the target table, (2) nonlinear interpolations are considered to reflect temporal changes, and (3) there is a need for depicting the propagation relationship between Ghosh model and the IOT-related models. In these regards, the modified MTT (MMTT) method realizes the following contents, including (1) probing into and then establishing a matrix-based economic structure (i.e., matrix-based links among intermediate input-outputs, final demand and value-added); (2) emphasizing economic structure changes over time; (3) adding up in the situation where the final demand signs are inconsistent between the prior table and the target table; (4) making sense regardless of whether the data assumptions are linear or nonlinear; (5) depicting the propagation relationship between Ghosh model and the IOT-related models; and (6) tracing structure changes of final demand and value added through the matrix-based linking method. Besides, the Fourier-Markov model is a mathematical technique for predicting the future values of a time series when the difference between the forecasts from basic models and initial estimates is taken into consideration (Lin et al., 2001; Su et al., 2002). This method has been conceived as a way of enhancing the accuracy of forecasting (Hsu et al., 2009). Thus, Fourier-Markov model could be combined with MMTT to construct the BAU scenario. But at the same time, the previous Fourier-Markov method cannot guarantee the accuracy of each observation, cannot ensure the constant good performance when compared with its original model that is based on, and will decrease the scope of application as its current form is not specified in a broad manner. Therefore, to address these weaknesses, we propose an element-based Fourier-Markov (EFM) method. Also, the EFM method could be applied regardless of whether the amount of data is large or not, which retains the advantages of the Fourier-Markov method (Lin et al., 2001; Su et al., 2002; Hsu et al., 2009). Besides, the EFM method could be used in the context of short- and long-term forecasting because the conversion matrix in the Markov process and the input parameters of the basic module of the Fourier-Markov method could be adjusted according to the changes in future trends (Alfieri et al., 2015; Z. Zhang et al., 2021; Rahnama, 2021). Then, BAU scenario could be validated by combining MMTT with Monte Carlo simulations (Wilting, 2012b), which provide more statistical information about the results.

The policy-related scenario could be constructed integrating IOA with the multi-objective optimization method. In the context of environment, CO_2 emissions alleviation is closely related to the trade-offs of economy-energy-environment (3E) system (S.-F. Zhang et al., 2019; Ye et al., 2019; Ning et al., 2020), which has been explored in the multi-objective optimization context (Mi et al., 2015; S.-W. Yu et al., 2018b). At the same time, research on factors affecting CO_2 emissions has found that more policy-related parameters could be comprehended from the 3E nexus (Mao et al., 2014, 2021). These policy-related parameters include CO_2 emission intensity targets, energy intensity targets, energy consumption cap targets, and the share of non-fossil fuel in primary energy consumption (Zhou et al., 2012; Mi et al., 2017c; Qi et al., 2020; Liu et al., 2022). Here, the multi-objective optimization method could be modified by including all of these parameters, so as to reflect the impacts of these parameters on CO_2 emissions reduction (Z.-Y. Li et al., 2021), and the trade-offs among 3E system (Mao et al., 2014). Also, this modification is supportive in the construction of input-output policy-related scenario through interconnecting production with consumption (Mao et al., 2014, 2021).

The problem-specific scenarios in terms of CO_2 emissions alleviation could be diverse, depending on how to reflect different decision preferences among multiple attributes when CO_2 emissions are allocated to sectors (Zhao et al., 2017). In this sense, the problem-specific scenarios could be arranged using the integration of IOA and multi-attribute decision making (MADM) methods (Yu et al., 2016b; S.-W. Yu et al., 2018b). In detail, to achieve the aggregate CO_2 emissions intensity target, some methods are proposed to transform this target into regional (Yi et al., 2011; Zhang et al., 2014) or sectoral endeavours (Zhao et al., 2017). This research emphasises the importance of allocating CO_2 emissions from the perspective of production-based CO_2 emissions accounting. Although many studies support the necessity of analysing sector-level impacts on CO_2 emissions reduction (Zhao et al., 2017; Song et al., 2018; Chen et al., 2020; W.-H. Xu et al., 2021; Fang et al., 2022), current input-output future scenarios have not considered the role of sector-level CO_2 emissions intensities in CO_2 emissions alleviation. That is, the sector-level CO_2 emissions intensities are forecasted, rather than considered as the additional directions towards CO_2 emissions alleviation (Ouyang and Lin, 2015; Zhao et al., 2017; Chen et al., 2020). For example, the energy intensity targets have been proposed for energy-intensive sectors for energy conservation and CO_2 emissions reduction in China (Ouyang and Lin, 2015; Chen et al., 2020). In these regards, the problem-specific scenarios could be arranged as the third category of input-output future scenarios by integrating IOA with MADM. This integrating method could be achieved by proposing a multi-attribute importance method (Yi et al., 2011; Zhao et al., 2017). This is also an aspect of interconnecting production with consumption (Oliveira et al., 2016; Rojas Sánchez et al., 2019). Besides, to arrange problem-specific scenarios, different decision preferences need to be specified among multiple criteria (Zhao et al., 2017). During this process, although traversing all the potential decision preferences is needed and feasible, current studies have not included the whole set of decision preferences. As such, when specifying all the potential decision preferences, the generalized weighting method (Zhang et al., 2004) in relation to permutation and combination is proposed (Yi et al., 2011; Yu et al., 2016b).

1.2.3.3. Input-output future configuring system construction for low-carbon economy

A configuration represents a number of specific and separate attributes which are meaningful collectively rather than individually (Rosenberg, 1968; Miller and Friesen, 1978), which contains relationships among elements or items representing multiple domains (Dess et al., 1993). Elements or items from a configurational perspective are conceived as constellations of inter-connected internal and external structures, and a configurational perspective has a predictive importance (Miller, 1990; Delery and Doty, 1996). In this sense, a configurational perspective could be developed towards tracking the development of organizations when the organizations are affected by the internal and external changes over time (C. Zhang et al., 2017). Not only is a configuration perspective popular in organizational theory and strategy research (Fiss, 2007), but it is also used in other fields, such as the economy (F.-F. Jiang et al., 2021), energy (Kimmich and Tomas, 2019), and environment (J.-F. Wu et al., 2021).

From a configurational perspective, the input-output future configuring system within a SAM scheme develops towards a system of multidimensionality; meanwhile the role of economic activity-level interdependencies adds up in this system. Besides, the input-output system is expected to respond to the temporal changes internally and externally to reflect the system-level evolution. But at the same time, a configurational perspective per se does not emphasize the optimization of a system, so there is a need for optimizing this input-output system to develop the configurational perspective (Hristu-Varsakelis et al., 2012). In this regard, the detailed, holistic, integrated image of this system is yielded (Bensaou and Venkatraman, 1995; F.-F. Jiang et al., 2021), promoting the effectiveness of this system.

Based on the previous studies, for the construction of input-output future configuring system, a configurational perspective is exploited and integrated into input-output system; meanwhile the characteristics of input-output system are retained. Also, the prospective feature of this system could be reflected and utilized for impact analysis and planning. Then, the influencing variables to consider could be processed following the formed input-output configuring procedure, so as to meet the specified adjustments (Xiao et al., 2017; Lin and Jia, 2018, 2020). Besides, during the construction of input-output future configuring system, the optimization feature of this system is achieved (Wang et al., 2010; H.-S. Lin et al., 2020), further developing the configurational perspective.

Optimization models have been incorporated into input-output systems, which allows for the optimal performance of economic activities when making choices as to constraints (Ochitwa, 1984; Nguyen et al., 2018). The related studies could be classified into two categories: one is for what if scenarios and the other is for what best scenarios (Pulido-Velazquez et al., 2008). Models for the former category are better suitable to reproduce the modus operandi of the system under the current institutional settings (Nguyen et al., 2018; Kang et al., 2020). By contrast, models for the latter category are useful to systematically search for the promising planning and management solutions (San Cristóbal, 2010; Yu et al., 2016b). The integration of mathematical programming with input-output system has been gradually extended to analyse the sector-level impacts of countermeasures (San Cristóbal, 2012), provide the applicability as a management avenue (Singh and Panda, 1989), and improve the efficiency of decision making (Hristu-Varsakelis et al., 2012). Compared to social accounting matrices, input-output tables are more widely used in this integration, although the former delineate both product and income values for an economy system comprehension (Sharify, 2021).

Computable general equilibrium (CGE) model is a useful tool for studying economic activity-level interdependence and general equilibrium repercussions in depth (Cardenete et al., 2017). The product and income flows between economic activities are of necessity for the CGE model, delineating the mutual influence and interdependence among various economic activities (Liang et al., 2022). Within a CGE appraisal, the economy consists of supply and demand is equalized across interconnected markets in the economy, and the abstract general equilibrium structure is combined with realistic economic data to solve numerically for the levels of supply, demand and price that support equilibrium across a specified set of markets (Cheng et al., 2015). CGE model has been widely used in diverse fields such as economy (L.-G. Zhang et al., 2018), energy (Lin and Jia, 2020), and environment (Xiao et al., 2017).

CGE model is built on the basis of SAM. Within a SAM scheme, the economic transactions are captured and the SAM optimization method is conducted for economic planning (Sharify, 2021). SAM optimization approach combines SAM with mathematical programming to attain the optimum level when considering goals and constraints, which improves CGE model encompassing the general equilibrium of economic activities. Also, because SAM reflects both product as well as income flows, the SAM optimization method has the capability of responding to these reflections for the purpose of planning.

However, there are two points which previous studies have not attached enough attention on. First, previous studies are less prone to study the importance of the predictability of the SAM optimization method (Ochitwa, 1984). Second, previous studies have not emphasized more on integrating CGE with SAM optimization, although this integration is capable of encompassing the advantages of both models (Sharify and Batey, 2006). So, in this study, we construct the input-output future configuring system, which is achieved by integrating CGE with SAM optimization. In this regard, this input-output future configuring system could utilize the merits of SAM, mathematical programming and CGE for impact analysis and management.

Low-carbon economy (LCE) is to achieve more economic outcomes, higher living quality, less depletion of natural resources, and less environmental contamination (UK Department Trade, 2003; Peng and Deng, 2021). Quantifying the LCE performance is of significance as this quantification could not only help comprehend the development of LCE, but also help the management for LCE. In detail, the LCE system has been constructed considering economy, society, energy and environment subsystems, so as to provide a systematic framework for CO_2 reduction and low-carbon transition (Shi et al., 2022). Also, the composite index for LCE has been perceived as useful for evaluating low-carbon development (Tan et al., 2017).

However, current quantifying LCE performance has not concentrated more on the optimization of LCE performance, which decreases the applicability of these useful methods to improve LCE performance. When it comes to how to achieve the optimization of LCE performance, not only does this corresponding method highlight the role of economy, society, energy, and environment (Tan et al., 2017; Shi et al., 2022), but it also encompasses the optimization of the composite index to establish. The latter, in particular, has been achieved in the field of energy (Wang et al., 2010; H.-S. Lin et al., 2020). Then, regarding the composite index to establish for LCE performance, previous studies have pointed out the usefulness of the indicators such as economic value per unit of CO_2 emissions (Heil and Wodon, 1997), energy consumption per unit of CO_2 emissions (Feng et al., 2015), and disposable income (for social welfare) per unit of CO_2 emissions (Ürge-Vorsatz et al., 2016; Zhou et al., 2017). The indicators depict the relationships with regard to the role of economy, energy and society in CO_2 emissions. The higher value of these indicators show the better performance of LCE.

Also, it is noted that there is a need for quantifying role of planning-based parameters in improving LCE performance. In the context of LCE in China, the planning-based parameters include the planning in terms of economy, energy, and CO_2 emissions. Because there are relations among economy, energy and CO_2 emissions, the optimum situation delineating the synergic effects of these contributing factors could be gained for better LCE performance.

1.2.4. Exploring carbon development measures from retrospect to prospect

1.2.4.1. Identifying CO_2 clusters changes

Using IOTs to identify key sectors and paths has attracted increasing attention in reducing CO_2 emissions (Kagawa et al., 2015; J.-S. Li et al., 2018; Liu et al., 2020). Identifying changes in CO_2 clusters could also be useful in CO_2 emissions reduction, which is achieved by cluster analysis. Cluster analysis is used as an approach to efficiently allocating the attention of reducing emissions by clusters (Shao et al., 2014; Kagawa et al., 2015). Cluster analysis provides insights to understand the role of economic structure in emissions reduction, as this method unravels the detailed composition of CO_2 clusters and reflects the underlying structure in CO_2 emissions (Fernau and Samson, 1990; Shao et al., 2014). Over time, there may exist sector heterogeneity in emissions (e.g., lock-in, catch-up and unlocking effects) (Chen et al., 2011; Z. Liu et al., 2015; H. Wang et al., 2020). Cluster analysis conducted at several years could reveal the possible lock-in, catch-up and unlocking effects in emissions, which supports the necessity of reducing CO_2 emissions through sectoral structure adjustments (Chang and Li, 2017) and sector-level upgrading (Liu and Wang, 2017). Lastly, when cluster analysis is performed from production, consumption and income perspectives, it helps understand and utilize the single, dual or multiple characteristics of sectors in CO_2 emissions reduction (J.-S. Li et al., 2018). These identified sectoral features contribute to improving the efficiency and effectiveness of emissions reduction.

Besides the carbon implications directly based on CO_2 clusters changes, there is a need to construct a link between the cluster-based carbon abatement and inter-sector linkage-based CO_2 emissions alleviation. Previous studies have emphasized the importance of transmission sectors along the supply chain rather than the exclusive concentration on the connection between the beginning and end of the supply chain (S. Liang et al., 2016), and have supported inter-sectoral linkages could be considered when deploying sector-specific CO_2 emission reduction efforts (S. Liang et al., 2015). In this way, the consideration about the role of each sector participating in a IOT-based framework is included. Despite that, previous studies could not allow for the exact impacts of transmission sectors and inter-sector linkages being integrated into the framework of IOT (S. Liang et al., 2015, 2016). Thus, the targeted and operable countermeasures could not be directly attained. So to enhance the efficacy of CO_2 emissions reduction, the integrated impacts of each sector could be figured out through incorporating the role of transmission sectors and the inter-sectoral linkages into CO_2 clusters.

When it comes to identifying CO_2 clusters changes, both methods and perspectives are worth attention. In the aspect of methods, statistical clustering methods (Shao et al., 2014; Kagawa et al., 2015) is a helpful consideration, and another one is by using sector characteristics (e.g., the classification of sectors into heavy, light, construction and service industries) (S.-J. Wang et al., 2019). Subsequently, the temporal changes in CO_2 clusters could be explored (Liang et al., 2013) by identifying the importance of possible lock-in, catch-up and unlocking effects, so as to support the necessity of reducing CO_2 emissions through sectoral structure adjustments (Chang and Li, 2017) and sector-level upgrading (Liu and Wang, 2017). In the aspect of perspectives, the production perspective is insightful (Shao et al., 2014; Kagawa et al., 2015), but the joint perspective in regard to production, consumption and income is also a potential effort in reducing CO_2 emissions given that each single perspective has its own merits, foci and practical scopes for CO_2 emissions reduction (J.-S. Li et al., 2018). This is because the Leontief model is demand-driven while the Ghosh model is supply-driven, and the two models unravel the economic system together (Miller and Blair, 2009). Hence, this joint perspectives helps understand and utilize the single, dual or multiple characteristics of sectors in CO_2 emissions reduction (J.-S. Li et al., 2018). Besides, urban household consumption has played an increasingly important role in CO_2 emissions in China (X.-Y. Liu et al., 2019). In this sense, identifying CO_2 clusters driven by urban household consumption is also vital.

Based on the identification of CO_2 clusters changes, utilizing the inter-sector linkage-based carbon abatement measures could enhance the efficacy of CO_2 emissions reduction. Sectoral CO_2 emissions accounting has been conducted from production-, consumption-, income-, and transmission-based perspectives (S. Liang et al., 2016; Shan et al., 2018; J.-S. Li et al., 2018). But at the same time, the connection between CO_2 clusters and sectoral CO_2 emissions has not been constructed from the perspective of the sector-level integrated impacts originating from the inter-sector CO_2 emissions flows. So the corresponding effective way of reducing CO_2 emissions could not be informed. Regarding the construction of this connection, previous studies have focused on the role of transmission sector in CO_2 emissions reduction thorough introducing the notion of betweenness which refers to as the importance of sectors in an economy as transmission centres (S. Liang et al., 2016). But previous studies could not allow for the exact impacts of transmission sectors being integrated into the framework of IOT, which could not form the direct connections with where to put efforts in alleviating CO_2 emissions within the IOT-based framework (S. Liang et al., 2016). This makes it difficult to attain the countermeasures in a straightforward manner which is better at managing the participation of each sector (Keček et al., 2022). Despite that, it is feasible to construct the connection by incorporating the concept of betweenness and inter-sector linkages into CO_2 clusters. In detail, this study could traverse the impacts of each sector and then conduct the inter-sector comparisons by way of dynamic programming, so as to enhance the efficacy of CO_2 emissions reduction.

1.2.4.2. Extending multiplier decomposition analysis and structural path analysis

In common with the construction and validation procedures of time-series SAMs, the related applications procedure could take into consideration a forward-backward perspective. One direct manifestation is that the extensions of multiplier decomposition analysis (MDA) and structural path analysis (SPA) to the supply-driven case could supplement the applications of MDA and SPA to the demand-driven case. The demand-driven model is used to evaluate the changes in the distribution of production, income and employment because of various measures undertaken affecting the exogenous income levels (Roland-Holst and Sancho, 1995; Fernández-Macho et al., 2008), while the supply-driven model is used to detect the effects on downstream sectors due to an estimated change in the exogenous costs (Roland-Holst and Sancho, 1995; Acquaye et al., 2017). MDA and SPA, the two widely used methods in the context of SAMs, have been extended from the demand-driven to supply-driven case (Defourny and Thorbecke, 1984; Roland-Holst and Sancho, 1995). MDA is used to capture the effects among and between economic activities within a structure, given an initial injection from exogenous variables (Blancas, 2006). MDA decomposes the total multipliers into four parts including the initial injection effect, the transfer multiplier effect, the open-loop multiplier effect and the closed-loop multiplier effect. SPA is used to explore the effects of paths on the economic system. Different perspectives are applied to study SPA. One viewpoint focuses on the partition of influences between two nodes within an economy into direct, total and global influences, and the other concentrates on tracking the paths through multiple tiers (Defourny and Thorbecke, 1984; Roland-Holst and Sancho, 1995). The latter emphasizes the identification and specification of key paths (Roland-Holst and Sancho, 1995).

When broadening the applications of MDA and SPA, there are some concerns. First, studies tend to compare MDA with SPA to investigate the economy (Defourny and Thorbecke, 1984), because more attention is concentrated to the superiority of one method over the other. However, MDA and SPA could help provide diverse channels for understanding how the economy operates, and, in the field of CO_2 emissions, how to orient the direction of emissions reduction. Second, it is found that the matrix-based arrangements when extending MDA and SPA to the supply-driven case do not give priorities to the convenience of results interpretation (Roland-Holst and Sancho, 1995; Miller and Blair, 2009), because the interpretation of results is inconsistent with the calculation of MDA and SPA in the supply-driven case. Last, in the field of CO_2 emissions, MDA and SPA were usually utilized from the demand-driven perspective, rather than the supply-driven perspective (Lenzen, 2003; Y.-Z. Li et al., 2018). Thus, insights from the latter perspective are not formed (Zhen and Li, 2021).

1.2.4.3. CO_2 inventories construction using a new subsystem decomposition analysis

CO_2 inventories are constructed from the production-based perspective, which facilitate the measures to mitigate CO_2 emissions (Shan et al., 2016; Y. Li et al., 2017; Shan et al., 2018). These series of CO_2 inventories, for example, have detailed energy- and process-related emissions (Shan et al., 2018). Further, the production-based CO_2 inventories contributes to developing the baseline, projecting CO_2 emissions, assessing the policy options, and establishing feasible mitigation targets (Y. Li et al., 2017; Chen et al., 2017). Despite the efficacy, production-based CO_2 inventories does not exhibit the full picture of emissions (B. Zhang et al., 2018). As a supplementary, environmentally-extended input-output models helps investigate the sector-level CO_2 emissions from consumption- and income-based perspectives, identifying main targets of CO_2 emissions mitigation measures (Chen et al., 2019). Taken together, there is a need to translate consumption- and income-based emissions at the sector level into the corresponding sector-level CO_2 inventories from past to future, in order to complement production-based CO_2 inventories in decision-making (Y. Li et al., 2017; B. Zhang et al., 2018).

Considering the characteristics and functions of production-based CO_2 inventories, consumption- or income-based CO_2 inventories could be formed as a detailed decomposition of total emissions. In this sense, subsystem analysis, initially proposed in (Sraffa, 1960), is with respect to the study of a sector or a group of sectors considered as a subsystem interacting with the rest of the sectors (Butnar and Llop, 2011), which helps comprehend the importance of a particular unit to the whole economic system (Alcántara and Padilla, 2009). There are three categories of methods for subsystem analysis. The first approach is utilized to quantify the relations between a specific subsystem and the rest of the whole system, which does not highlight the interconnections induced by each sector (Butnar and Llop, 2011). Although the rest approaches investigate the role of each sector in the whole economic system, they differ in exploring the contributions of the internal and feedback components to the total influences of a specific sector (Sanchez-Choliz, 2003; Alcántara et al., 2017). The idea behind the approach in (Sanchez-Choliz, 2003) is consistent with that from (Alcántara and Padilla, 2009), and also it finds supports in the area of structural path analysis (Lenzen, 2007). But in the meantime, the approach in (Sanchez-Choliz, 2003) has not been applied in the context of the supply-driven model (i.e., Ghosh model). In this regard, the economic system is only explored by demand-driven model (i.e., Leontief model), in which the economy-wide effects arising from final demand, rather than primary inputs, are investigated (Andrés et al., 2021).

Despite the effectiveness of the subsystem analysis in decomposing variables, this analytical method does not evaluate the contributions of influencing factors behind temporal changes in the variables to decompose. To achieve the decomposition of changes, subsystem analysis could be further combined with structural decomposition analysis (SDA). SDA is a decomposition technique related to quantifying both direct and indirect effects of factors on the temporal changes in variables (Zhang, 2010; Cansino et al., 2016). In the field of CO_2 emissions, some studies have extended subsystem analysis by way of SDA, but their studies consider the performance of a group of sectors, rather than sector-specific performance (Butnar and Llop, 2011). In this sense, it is unclear how sector-level CO_2 emissions transmit throughout the economic system. Also, this integrated model is proposed in the demand-driven case, without emphasizing the implications from the supply-driven model. Thus, the decomposition of emissions changes induced by sector-level primary inputs is not informed, thereby decreasing the scope of use in decision-making (Zhang, 2010).

1.2.4.4. Carbon management under multi-criteria decision making

During the procedure of integrating IOA and scenario analysis, multi-criteria decision making (MCDM) has been found to be feasible and useful. This is because not only does MCDM suit the real world problems involving multiple, conflicting and incommensurable objectives (Oliveira and Antunes, 2004; San Cristóbal, 2012; Oliveira et al., 2016), but this technique also provides an approach towards the trade-offs among multiple attributes and multiple objectives (Weng et al., 2010; De Carvalho et al., 2016; Abdullah et al., 2021). For example, multi-attribute decision making methods (i.e., the first category of MCDM) are used to allocate CO_2 emissions among sectors by considering the impacts of various attributes in terms of capacity, responsibility, and potential (Zhao et al., 2017). For another example, multi-objective optimization methods (i.e., the second category of MCDM) are used to investigate whether energy savings goal is achieved when the decision-making process is confronted with multiple objectives in terms of economy, energy and environment (S.-W. Yu et al., 2018b).

However, it is also noted that the interconnections between production and consumption have not been emphasized during the process where IOA is integrated with scenario analysis by means of MCDM, despite these interconnections fundamentally characterizing the IOA scheme and related extensions to environment (Oliveira and Antunes, 2004; Weng et al., 2010; Carvalho et al., 2015; Oliveira et al., 2016; Rojas Sánchez et al., 2019). Further, corresponding to the interconnections between production and consumption within input-output future scenarios, some concerns need to be dealt with. First, for the 'business-as-usual' (BAU) scenario, temporal changes of economic system depicted by input-output tables could be considered (Zhao et al., 2017; Song et al., 2018; C. Li et al., 2021). Second, in the policy-related scenario, the reflection of multiple policy-related parameters in the multi-objective optimization models could be further explored. For example, carbon emissions have been found to be impacted by policy-related parameters, such as CO_2 emissions intensity target (Mi et al., 2017c), energy intensity target (Liu et al., 2022), energy consumption cap targets (Qi et al., 2020), and the share of non-fossil fuels in the total energy consumption (Zhou et al., 2012). But the impacts of these multiple policy-related parameters on CO_2 emissions have not been investigated. Finally, as for the problem-specific scenarios by multi-attribute decision making, although decision preferences are considered in form of the specification of weights under proper transformation functions (Parreiras and Vasconcelos, 2009; Yu et al., 2016b), the role of permutation and combination in specifying the potential scenarios could be emphasized (Yi et al., 2011). In this way, all the potential contexts are included since the number of external variables is not relatively large. Meanwhile, to fulfil the problem-specific objective, a multi-attribute importance method could be constructed. With this model, not only could the importance of each specified scenario be quantified, but the importance could also be allocated among sectors (Yi et al., 2011; Zhao et al., 2017).

As one application of input-output future scenarios, CO_2 emissions synergistic alleviation could be explored during the integration of IOA and scenarios analysis by way of MCDM, when considering the economy-energy-environment (3E) nexus (Dong et al., 2014; Carvalho et al., 2015; Rojas Sánchez et al., 2019; X. Li et al., 2021). Meanwhile, within the established 3E nexus framework, allocating CO_2 emissions reduction targets to each sector is an important way to complete carbon emissions reduction task (Zhao et al., 2017). During this allocation process, CO_2 emissions alleviation requires the synergies among sectors (Ning et al., 2019; Dong et al., 2023). The industrial synergistic development is characterised the interaction, independence and mutual support between sectors (Lin and Teng, 2023), which could be reflected by applying IOA and related input-output future scenarios (Yin et al., 2022). It is because IOA in the scenario context could manifest the flows of goods and services among sectors and demonstrate the sectoral interdependence within the economic structure (Jensen et al., 1988). However, despite that the importance of exploring the path of synergistic carbon emissions reduction of multiple sectors to improve carbon emission reduction efficiency has been recognized (Dong et al., 2023), previous studies have not conducted the exploration of sector-level CO_2 emissions synergistic alleviation. Also, the dynamics featuring the synergy of reducing CO_2 emissions among sectors has not been emphasized although the dynamical effects are supposed to be captured to facilitate CO_2 emissions abatement (M.-H. Jiang et al., 2021).

To address these weaknesses, the overview of changes in CO_2 emissions is provided, and the direction and channels identifications are attained by means of the shift-share analysis (SSA). SSA is a technique that focuses on partitioning the growth in an economic variable in a particular area into various components when considering the changes in the variable as a dynamic progress (Creamer, 1943; Yavas et al., 1992; Lin et al., 2019). This growth is decomposed into national growth, industrial mix, and competitive position effects. Thus, with the SSA method, the determinants of growth and decline could be figured out. Also, this method enables to identify the key sectors which contribute to the changes in variables and to grasp both the direction about how the future develops as well as the principle of adjusting industrial structure.

However, due to the existence of interwoven effect in industrial mix and competitive position effects, the Esteban-Marquillas version of SSA is proposed by introducing homothetic variables to deal with component independence (Esteban-Marquillas, 1972; Sheng et al., 2021). Also, when SSA is used as a comparative static approach, which considers conditions only at the beginning and end years of the time period, the SSA method influences the allocation of changes in variables among the three shift-share effects (Barff and Iii, 1988). Thus, the dynamics is introduced to the Esteban-Marquillas shift-share extension. But at the same time, when it comes to the application of this dynamic Esteban-Marquillas method to evaluating changes in CO_2 emissions, previous studies have not taken this aspect into consideration although the SSA method has been used in diverse fields, including economy, energy and environment (Li and Huang, 2010; H. Li et al., 2017; Lin et al., 2019).

1.2.4.5. CO_2 emissions reduction from the perspective of low-carbon economy

Input-output optimization for forecasting has attracted increasing interest in low-carbon economy (LCE) study (Y.-Q. Su et al., 2021). To illustrate, the low-carbon scenarios are developed to define and establish the feasible countermeasures (Nguyen et al., 2018). The low-carbon measures under multiple constraints are evaluated for determining the optimum situations (Kang et al., 2020). The socio-economic impacts for CO_2 emissions peak are assessed for investigating the pathways in which CO_2 emissions peak could be achieved (Mi et al., 2017c; S.-W. Yu et al., 2018a). The effects of CO_2 emissions on resources are optimized for addressing the changes from climate change (Aviso et al., 2018). The influences of CO_2 abatement measures are gauged through achieving general equilibrium (Dong et al., 2017).

However, there are still some attempts to make for input-output forecasting studies in the context of LCE. First, despite the significance of composite indicators has been recognized (Wang et al., 2010; H.-S. Lin et al., 2020), the optimization of composite indicators has not been undertaken in input-output forecasting studies. Second, although the role of energy intensity and CO_2 intensity in CO_2 emission reduction has drawn the attention (Xiao et al., 2017; Li et al., 2019), the relation among energy intensity, CO_2 intensity, total energy consumption, and the growth rate of GDP has not been investigated for the optimum situations. Third, because computable general equilibrium (CGE) model focuses on general equilibrium, rather than a pursuit of optimization (Sharify and Batey, 2006), the SAM optimization model could improve this point by integrating CGE with optimization.

These aforementioned attempts constitute the key features of a new input-output forecasting method, which is what we have termed input-output future configuring system in this study, corresponding to the connotation of configuration in the organizational theory (Rosenberg, 1968; Miller and Friesen, 1978). This system could fulfil the following aspects. First, the effects in terms of volume and structure could be reflected to help with the countermeasures design (Li et al., 2019; Y.-Q. Su et al., 2021). Second, the future trends at sector level in the context of LCE could be delineated to facilitate the preparation for future changes (San Cristóbal, 2010; Igos et al., 2015).

Third, this system could attain adjustments and achieve flexibilities when the influencing variables are changed (Singh and Panda, 1989).

1.3. Research objectives and thesis structure

The objectives of this thesis are to construct time-series IOTs and SAMs from the viewpoints of retrospect and prospect, and correspondingly, to explore carbon development measures by extending time-series IOTs and SAMs. Because differing focusses exist between IOT and SAM, the aforementioned objectives need to be specialized, so as to provide specific solutions to time-series input-output systems construction, validation and applications. But at the same time, there are interconnections between IOT and SAM. This consideration not only emphasizes the harmonization of differing input-output systems, but also potentially expands the practical scopes. For example, the techniques for exploring carbon development measures from retrospect to prospect are effective for both input-output systems. Therefore, the objectives are specialized and categorized, which are explained by thesis structure and highlights. Correspondingly, each chapter (Chapters 2 to 6) takes the form of five sections, which includes introduction, literature review, method and data, results and discussion, and conclusions.

(1) Chapter 2 updates time-series input-output tables with economic structure concerns and identifies changes in CO_2 clusters. The methods improvements are as follows:

- Matrix transpose is for modifying matrix transformation technique (MTT)
- The modified MTT (MMTT) method is reinforced by reflecting price fluctuations
- Matrix-based linking method updates final demand and value added categories
- Monte Carlo simulations with matrix calculation methods are for the validation process
- CO_2 clusters changes are identified from production, consumption and income perspectives

(2) Chapter 3 attains a forward-backward realization of solutions to time-series social accounting matrices construction, validation and applications. The methods improvements are as follows:

- Matrix-induced structure is proposed to construct time-series SAMs
- K-nearest-neighbour algorithm and cross validation are joint to impute time-series SAMs
- A new matrix calculation method is proposed to conduct time-series SAMs validation
- Demand- and supply-driven CO_2 emissions are analysed using multipliers, tiers and paths

(3) Chapter 4 focuses on input-output forecasting and CO_2 inventories construction using a new subsystem decomposition method, which includes:

- An element-based Fourier-Markov method is for IOTs and SAMs forecasts
- The modified MTT (MMTT) method with T-accounts concept is proposed for trends structuring
- Matrix calculation methods with Monte Carlo simulations validate input-output forecasts
- A subsystem analysis with structural decomposition analysis is proposed for CO_2 inventories

(4) Chapter 5 presents an integrated scheme of input-output future scenarios construction interconnecting production with consumption and analyses sector-level CO_2 emissions synergistic alleviation. The detailed techniques are proposed as follows:

- An integrated scheme is for constructing input-output future scenarios
- A procedure of input-output forecasting is applied to BAU scenario
- Extended multi-objective optimization is used for policy-related scenario
- A multi-attribute importance method is proposed for problem-specific scenarios

- CO_2 emissions reduction at the sector level is analysed in constructed scenarios

(5) Chapter 6 covers an input-output future configuring system for low-carbon economy using a social accounting matrix optimization design. The methodological improvements are proposed as follows:

- Input-output future configuring system is constructed to reflect and reconcile future trends
- A social accounting matrix optimization design is proposed for the system construction
- Monte Carlo simulation is conducted to validate input-output future configuring system
- Element-based Fourier-Markov method links simultaneous equations method to forecast
- Input-output future configuring system is applied to the low-carbon economy context

Chapter 2: Updating time-series input-output tables with economic structure concerns and identifying CO_2 clusters changes

2.1. Introduction

An input-output table (IOT) elaborates economic structure by depicting sectoral linkages affected by final use and value added (Leontief, 1986; Miller and Blair, 2009). Time-series IOTs help comprehend economic structures over time. In detail, they reflect the continuous sectoral interconnections within an economy (Harry and Keiko, 2015), are used as the long-term reference data for economy-related phenomena (Timmer et al., 2012), and provide data supports for econometric modelling (Hübler et al., 2022), social accounting matrix (Cho and Díaz, 2019), computable general equilibrium model (Hübler and Pothen, 2017), integrated assessment model (Capellán-Pérez et al., 2020), and other models (Lombardi et al., 2019). Meanwhile, time-series IOTs are of importance in diverse contexts, such as exploring energy consumption (Meng et al., 2020), investigating greenhouse gas emissions (Wiedmann et al., 2010), measuring environmental sustainability performance (Acquaye et al., 2017), and assessing sustainability impacts (Egilmez et al., 2020).

However, IOTs are always data with time intervals (Lenzen et al., 2012). To achieve the significance of time-series IOTs, construction and validation approaches are proposed (Ahmad, 2002; Harry and Keiko, 2015; Lenzen et al., 2009; Timmer et al., 2012; Tukker et al., 2013; Wood et al., 2014). But the concerns related to economic structure are still needed. Economic structure is defined as the composition and patterns of various components of the economy such as: production, consumption, investment, trade and gross domestic product (Su, 1970; Thakur, 2008; Thakur and Alvayay, 2012). Specially, IOT has been conceived as a detailed empirical representation of economic structure by presenting economic dependence such as inter-sector flows and matrix-based links among intermediate input-outputs, final demand and value added (Jensen et al., 1988;

Kim and Kim, 2015; Wang et al., 2015a). In this sense, the concerns related to economic structure tend to be the necessary consideration when conducting input-output analysis, and exploring the fundamental and crucial connections with building time-series IOTs.

Against this backdrop above, the economic structure concerns during updating IOTs are explained as follows. First, MTT (matrix transformation technique) simultaneously probes into a matrix-based economic structure (i.e., matrix-based links among intermediate input-outputs, final demand and value added) and emphasizes economic structure changes over time to construct time-series IOTs (Wang et al., 2015a). But the weaknesses of MTT arise when (1) final demand signs are inconsistent between the prior table and the target table, (2) nonlinear interpolations are considered to reflect temporal changes, and (3) there is a need for depicting the propagation relationship between Ghosh model and the IOT-related models. Hence, a new matrix calculation method is needed. Second, because structural transformation is measured at constant prices (Herrendorf et al., 2014), price fluctuations in IOTs need to be reflected. Third, to trace the structure changes of final demand and value added, the exact temporal impact of each element of final demand and value added needs to be captured and then linked with intermediate input-outputs. Thus, a matrix-based linking method is needed. Lastly, the validation analysis of time-series IOTs needs to be conducted in the context of the matrix-based structures of IOTs, so as to depict the direct and deterministic effects of variables in IOTs (Zheng et al., 2018).

Using IOTs to identify key sectors and paths has attracted increasing attention in reducing CO_2 emissions (Kagawa et al., 2015; J.-S. Li et al., 2018; Liu et al., 2020). Identifying changes in CO_2 clusters could also be useful in CO_2 emissions reduction, which is achieved by cluster analysis. In detail, for a certain year, cluster analysis is used as an approach to efficiently allocating the attention of reducing emissions by clusters (Shao et al., 2014; Kagawa et al., 2015). Meanwhile, cluster analysis provides a direction towards understanding the role of economic structure in emissions reduction, as this method unravels the detailed composition of CO_2 clusters and reflects the underlying structure in CO_2 emissions (Fernau and Samson, 1990; Shao et al., 2014). Then, over time, there may exist sector heterogeneity in emissions (e.g., lock-in, catch-up and unlocking effects) (Chen et al., 2011; Z. Liu et al., 2015; H. Wang et al., 2020). At this time, cluster analysis conducted at several years could reveal the possible lock-in, catch-up and unlocking effects in emissions, which supports the necessity of reducing CO_2 emissions through sectoral structure adjustments (Chang and Li, 2017) and sector-level upgrading (Liu and Wang, 2017). Lastly, when cluster analysis is performed from production, consumption and income perspectives, it helps understand and utilize the single, dual or multiple characteristics of sectors in CO_2 emissions reduction (J.-S. Li et al., 2018). In these regards, these identified sectoral features contribute to improving the efficiency and effectiveness of emissions reduction.

Besides the carbon implications directly based on CO_2 clusters changes, there is a need to construct a link between the cluster-based carbon abatement and inter-sector linkage-based CO_2 emissions alleviation. Previous studies have emphasized the importance of transmission sectors along the supply chain rather than the exclusive concentration on the connection between the beginning and end of the supply chain (S. Liang et al., 2016), and have supported inter-sectoral linkages could be considered when deploying sector-specific CO_2 emission reduction efforts (S. Liang et al., 2015). In this way, the consideration about the role of each sector participating in a IOT-based framework is included. Despite that, previous studies could not allow for the exact impacts of transmission sectors and inter-sector linkages being integrated into the framework of IOT (S. Liang et al., 2015, 2016). Thus, the targeted and operable countermeasures could not be directly attained. So to enhance the efficacy of CO_2 emissions reduction, the integrated impacts of each sector could be figured out through incorporating the role of transmission sectors and the inter-sectoral linkages into CO_2 clusters.

When it comes to China, updating time-series IOTs is necessary and meaningful, and so is identifying CO_2 clusters changes. First, official IOTs are with time intervals in China: benchmark IOTs (i.e., IOTs based on survey method) depict economy-wide sectoral linkages in the years whose last digits are 2 and 7, followed by extended IOTs (i.e., IOTs based on non-survey methods) every two years. Second, China has been experiencing structural transformation, and exerting increasingly pronounced impacts on economic development and environmental protection (Li and Lin, 2017; Zheng et al., 2009). Correspondingly, in sector-level CO_2 emissions reduction, identifying CO_2 clusters changes from the production perspective was insightful in curbing emissions (Shao et al., 2014; S.-J. Wang et al., 2019); there is still a need for exploring the use of time-series IOTs in terms of identifying CO_2 clusters changes from consumption- and income-based perspectives. Also, within the identified CO_2 clusters, the link between the cluster-based carbon abatement and inter-sector linkage-based CO_2 emissions alleviation could be constructed to promote CO_2 emissions reduction.

In this study, we utilize some economic structure concerns to update time-series IOTs. Specifically, a new matrix calculation method is proposed for tracking and establishing matrix-based links among intermediate input-outputs, final demand and value added. The method is reinforced by reflecting price fluctuations in IOTs. This method is further extended by proposing a matrix-based linking method to trace the structure changes of final demand and value added. The validation analysis of time-series IOTs is conducted in the context of the matrix-based structures of IOTs. Based on the time-series IOTs, CO_2 clusters changes from production, consumption and income perspectives are identified, deriving sector characteristics to reduce CO_2 emissions. This study is in the case of China from 1997 to 2020. The remainder of paper is organized as follows: Section 2.2 reviews the literature, Section 2.3 explains the methods and data, Section 2.4 is about results and discussion, and Section 2.5 provides conclusions.

2.2. Literature review

Many endeavours have been made to construct time-series IOTs. RAS (one bi-proportional matrix balancing technique) balances positive IOTs on the basis of sector-level gross outputs, and intermediate input-outputs (Ahmad, 2002; Miller and Blair, 2009; Timmer et al., 2012; Harry and Keiko, 2015). RAS extensions tackle negative IOTs and inconsistent constraints, such as GRAS (Tukker et al., 2013; Wood et al., 2014) and KRAS (Lenzen et al., 2009). The Leontief dynamic IO model improves static IO models by exploring intertemporal and inter-sectoral relations between capital change and technological levels (Leontief, 1986). For example, the Leontief IO model is extended by introducing new capital and labour matrices to explore impacts of technological progress (1997-2100) (Pan, 2006), and by introducing human capital to study dynamic relations between the education sector and other sectors (2000-2010) (Zhang and Chen, 2008). The dynamic IO model is established to closely fit specific questions, without enough focuses on releasing constraints from dynamic links between capital and technology (Leontief, 1986). MTT has been applied recently (Wang et al., 2015a; Zheng et al., 2018). Through a matrix calculation method, MTT tracks distributional impacts of sectoral value-added on intermediate economic transactions and final demand, forming a matrix-based structure. Also, MTT emphasizes economic structure changes over time, rather than the assumption that technological coefficients are stable in the time dimension.

Yet, the process of constructing time-series IOTs still needs some economic structure concerns. First, despite the novelty of MTT, the weaknesses of MTT arise when (1) final demand signs are inconsistent between two IOTs to use, (2) nonlinear interpolation is considered to reflect temporal changes, and (3) there is a need to depict the propagation relationship between Ghosh model and the IOT-related models. To reconcile this, a new matrix calculation method is needed. Second, as structural transformation is measured at constant prices (Herrendorf et al., 2014), price fluctuations in IOTs need to be reflected. Because the proposed new matrix calculation method establishes the matrix-based links among intermediate input-outputs, final demand and value added, price indices are applied directly in the matrix-based links when the matrix-based structure is preserved. Last, to trace the structure changes of final demand and value added, the exact temporal impacts of each element of final demand and value added need to be captured, and linked with intermediate input-outputs. The existing methods for updating the categories of final demand and value added are primarily for balancing the initial estimate at the aggregate level and do not emphasize economic structure changes (Huang et al., 2008; Wang et al., 2015a). Hence, a new matrix-based linking method is needed. The characteristics of this new method include achieving automatic and straightforward adjustments when capturing and linking structure changes, and reflecting linear and/or non-linear impacts over time.

The validation analysis of IOTs is conducted from various angles. In detail, matrix similarity indicators are applied to investigate the similarities among different versions of IOTs (Steen-Olsen et al., 2016). Statistical indicators for error estimation are utilized to understand the differences between estimated IOTs and referenced IOTs (Wang et al., 2015a). The Sherman-Morrison-Woodbury formula is applied in the sensitivity analysis by providing the impacts of each direct consumption coefficient (Wilting, 2012a). The matrix perturbation analysis is modified to study how environmentally extended IO model is sensitive to the changes of parameters (Mattila et al., 2013). Monte Carlo simulations are applied to the Leontief model to explore uncertainties of IOTs (Wilting, 2012a), which provide more statistical information about the results. Correspondingly, with the aim of depicting the direct and deterministic effects of variables to explore in the IOT framework (Zheng et al., 2018), Monte Carlo simulations could be utilized in the context of the matrix-based structures of IOTs.

For the application of time-series IOTs to identifying CO_2 clusters changes, both methods and perspectives are worth attention. In the aspect of methods, statistical clustering methods (Shao et al., 2014; Kagawa et al., 2015) is a helpful consideration, and another one is by using sector characteristics (e.g., the classification of sectors into heavy, light, construction and service industries) (S.-J. Wang et al., 2019). Subsequently, the temporal changes in CO_2 clusters could be explored (Liang et al., 2013) by identifying the importance of possible lock-in, catch-up and unlocking effects, so as to support the necessity of reducing CO_2 emissions through sectoral structure adjustments (Chang and Li, 2017) and sector-level upgrading (Liu and Wang, 2017). In the aspect of perspectives, the production perspective is insightful (Shao et al., 2014; Kagawa et al., 2015), but the joint perspective in regard to production, consumption and income is also a potential effort in reducing CO_2 emissions given that each single perspective has its own merits, foci and practical scopes for CO_2 emissions reduction (J.-S. Li et al., 2018). This is because the Leontief model is demand-driven while the Ghosh model is supply-driven, and the two models unravel the economic system together (Miller and Blair, 2009). Hence, this joint perspectives helps understand and utilize the single, dual or multiple characteristics of sectors in CO_2 emissions reduction (J.-S. Li et al., 2018). Besides, urban household consumption has played an increasingly important role in CO_2 emissions in China (X.-Y. Liu et al., 2019). In this sense, identifying CO_2 clusters driven by urban household consumption is also vital.

Based on the identification of CO_2 clusters changes, utilizing the inter-sector linkage-based carbon abatement measures could enhance the efficacy of CO_2 emissions reduction. Sectoral CO_2 emissions accounting has been conducted from production-, consumption-, income-, and transmission-based perspectives (S. Liang et al., 2016; Shan et al., 2018; J.-S. Li et al., 2018). But at the same time, the connection between CO_2 clusters and sectoral CO_2 emissions has not been constructed from the perspective of the sector-level integrated impacts originating from the inter-sector CO_2 emissions flows. So the corresponding effective way of reducing CO_2 emissions could not be informed. Regarding the construction of this connection, previous studies have focused on the role of transmission sector in CO_2 emissions reduction thorough introducing the notion of betweenness which refers to as the importance of sectors in an economy as transmission centres (S. Liang et al., 2016). But previous studies could not allow for the exact impacts of transmission sectors being integrated into the framework of IOT, which could not form the direct connections with where to put efforts in alleviating CO_2 emissions within the IOT-based framework (S. Liang et al., 2016). This makes it difficult to attain the countermeasures in a straightforward manner which is better at managing the participation of each sector (Keček et al., 2022). So it is necessary to construct the connection by incorporating the concept of betweenness and inter-sector linkages into CO_2 clusters. In detail, this study could traverse the impacts of each sector and then conduct the inter-sector comparisons by way of dynamic programming, so as to enhance the efficacy of CO_2 emissions reduction.

Based on the previous studies, to update time-series IOTs, this study proposes a new matrix calculation method on the basis of MTT and matrix transpose, tracking and establishing matrix-based links among intermediate input-outputs, final demand and value added. This modified MTT (MMTT) method is reinforced by reflecting price fluctuations in IOTs. Also, this method is further extended by proposing a matrix-based linking method to trace the structure changes of final demand and value added. In these regards, the MMTT method realizes the following contents, including (1) probing into and then establishing a matrix-based economic structure (i.e., matrix-based links among intermediate input-outputs, final demand and value-added); (2) emphasizing economic structure changes over time; (3) adding up in the situation where the final demand signs are inconsistent between the prior table and the target table; (4) making sense regardless of whether the data assumptions are linear or nonlinear; (5) depicting the propagation relationship between Ghosh model and the IOT-related models; and (6) tracing structure changes of final demand and value added through the matrix-based linking method. Then, the validation analysis of time-series IOTs is conducted using Monte Carlo simulations in the context of matrix-based structures of IOTs. Using the updated time-series IOTs, this study identifies CO_2 clusters changes from production, consumption and income perspectives and derives sector characteristics for CO_2 emissions reduction, which is achieved by cluster analysis and dynamic programming.

2.3. Method and data

2.3.1. Constructing time-series IOTs with MMTT

2.3.1.1. Modify MTT with matrix transpose and constant prices

Matrix transpose is used to modify MTT, which ensures that the modified MTT (MMTT) is still a matrix calculation method emphasizing structural changes and overcomes the three possible weaknesses of MTT (as introduced in Sections 2.1 and 2.2). Through the MMTT method, new matrix-based links among intermediate input-outputs, final demand and value added are tracked and established. Then, price indices are applied directly in the new matrix-based links because MMTT is a matrix calculation method. In this way, official IOTs (including benchmark and extended IOTs) at constant prices are achieved. Based on the IOTs constructed at constant prices, MMTT, in combination with linear interpolation method, is further applied to construct the IOTs at constant prices in unreported years. Related equations are as follows.

The initial matrix input, $\boldsymbol{X_0}$, is an $(n+1)\times(n+1)$ matrix with elements at current prices:

$$\boldsymbol{X_0} = \begin{bmatrix} \boldsymbol{D_0} & \boldsymbol{F_0} \\ \boldsymbol{V_0} & \boldsymbol{G_0} \end{bmatrix} \tag{2-1}$$

where $\boldsymbol{D_0}$ is an $n \times n$ matrix depicting intermediate input-outputs among n sectors, $\boldsymbol{F_0}$ represents an $n \times 1$ matrix denoting final demand, $\boldsymbol{V_0}$ is a $1 \times n$ matrix representing sector-level value added, and $\boldsymbol{G_0}$ is the total final demand.

We convert $\boldsymbol{X_0}$ into $\boldsymbol{Y}$ and then transpose $\boldsymbol{Y}$ as follows.

$$\boldsymbol{Y} = \begin{bmatrix} \boldsymbol{d} & \boldsymbol{v} \\ \boldsymbol{f} & \boldsymbol{g} \end{bmatrix} \tag{2-2}$$

where $\boldsymbol{d} = \left(\widehat{\boldsymbol{V_0}}\right)^{-1}\boldsymbol{D_0}$, $\boldsymbol{v}$ is an $n \times 1$ matrix with each element being one, $\boldsymbol{f} = \left(\widehat{\boldsymbol{G_0}}\right)^{-1}\boldsymbol{F_0}$, $\boldsymbol{g}$ equals one and ^ represents diagonalization of the vector.

$$\boldsymbol{N} = diag\left(1 - \sum\nolimits_i^n d_{1i}, 1 - \sum\nolimits_i^n d_{2i}, \cdots, 1 - \sum\nolimits_i^n d_{ni}\right) + \boldsymbol{d^T} \tag{2-3}$$

$$\boldsymbol{F_1} = \boldsymbol{N}\boldsymbol{V_1} \tag{2-4}$$

$$\boldsymbol{D_1} = \widehat{\boldsymbol{V_1}}\boldsymbol{d} \tag{2-5}$$

$$\boldsymbol{G_1} = \sum \boldsymbol{F_1} \tag{2-6}$$

where $\boldsymbol{D_1}$, $\boldsymbol{F_1}$, $\boldsymbol{V_1}$ and $\boldsymbol{G_1}$ are the intermediate input-outputs at constant prices, final demand at constant prices, value added at constant prices, and total final demand at constant prices respectively, and $\boldsymbol{d^T}$ means the transpose of the matrix $\boldsymbol{d}$. Correspondingly, $\boldsymbol{X_1}$ represents $\boldsymbol{X_0}$ at constant prices.

$$\boldsymbol{X_1} = \begin{bmatrix} \boldsymbol{D_1} & \boldsymbol{F_1} \\ \boldsymbol{V_1} & \boldsymbol{G_1} \end{bmatrix} \tag{2-7}$$

2.3.1.2. Extend the modified MTT with a matrix-based linking method

The MMTT method is further extended to capture the structure changes of final demand and value added by proposing a matrix-based linking method. First, the matrix-based linking method starts from the final demand and value added derived from the results of the MMTT method. Since this linking method is matrix-based, the links between the categories of final demand (or value added) and intermediate input-outputs are established in a direct and deterministic manner. Then, this matrix-based linking method investigates and then establishes the matrix-based structures of final demand (or value added), allowing positive and negative categories of final demand (or value added). Subsequently, the exact temporal impacts of each element of final demand and value added are calculated; meanwhile, the matrix-based structures are consistent with the results from the MMTT method. The characteristics of this matrix-based linking method include achieving automatic and straightforward adjustments when capturing and linking structure changes, and reflecting linear and/or non-linear impacts over time. Related equations are as follows.

$$\boldsymbol{U_{category}} = \begin{cases} \widehat{\boldsymbol{u_c}}\widehat{\boldsymbol{U_c}}\boldsymbol{u_n^*}(\widehat{\boldsymbol{u_n}})^{-1} & \boldsymbol{if}\ \ \boldsymbol{u_n} \neq \boldsymbol{0} \\ \widehat{\boldsymbol{u_c}}\boldsymbol{w_m}\boldsymbol{w_n} & \boldsymbol{if}\ \ \boldsymbol{u_n} = \boldsymbol{0} \end{cases} \tag{2-8}$$

$$\boldsymbol{U_c} = \left[\boldsymbol{U_c^p}, \boldsymbol{U_c^n}\right] \tag{2-9}$$

$$\boldsymbol{u_c} = \begin{bmatrix} \boldsymbol{u_p^d} \\ \boldsymbol{u_n^d} \end{bmatrix} \tag{2-10}$$

$$\boldsymbol{w_n} = \begin{bmatrix} \boldsymbol{u_m} \\ \boldsymbol{u_n^*} \end{bmatrix} \tag{2-11}$$

where $\boldsymbol{U_{category}}$ denote the categories of final demand (or value added) on the basis of the MMTT method and the matrix-based linking method, $\boldsymbol{u_n^*}$ is the vector for the sum of positive and negative values of final demand (or value added) updated by the MMTT method, $\boldsymbol{u_n}$ is the vector for the sum of positive and negative values of final demand (or value added) to update, $\boldsymbol{u_m}$ is the vector for the difference of positive and negative values of final demand (or value added) to update, $\boldsymbol{U_c^p}$ is the vector for the sum of positive values of final demand (or value added) to update, $\boldsymbol{U_c^n}$ is the vector for the sum of negative values of final demand (or value added) to update, $\boldsymbol{u_p^d}$ is the vector for the updated share of each positive final demand (or value added) category in total positive final demand (or value added), $\boldsymbol{u_n^d}$ is the vector for the updated share of each negative final demand (or value added) category in total final demand (or value added), and the new elements added at the end of $\boldsymbol{u_p^d}$ ($\boldsymbol{u_n^d}$) are zeros to form the complete $\boldsymbol{u_p^d}$ ($\boldsymbol{u_n^d}$) when the dimensions of $\boldsymbol{u_p^d}$ and $\boldsymbol{u_n^d}$ are different.

Then, $\boldsymbol{w_m}$ is calculated as follows.

$$\boldsymbol{w_m w_n} = \boldsymbol{w^{-1} w_n} \qquad (2-12)$$

where $\boldsymbol{w}$ is the matrix $\begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}$.

2.3.1.3. Modify constructed IOTs with technology sources

The constructed IOTs need to be converted to noncompetitive IOTs[1] by quantifying the impacts of imports on IOTs. Following the study (Su and Ang, 2013), the impacts of imports are distributed proportionally to the intermediate input-outputs and final demand categories, which is based on the import ratios as follows.

$$\boldsymbol{M} = diag\left(\left(\boldsymbol{D_1} + \boldsymbol{F_{category}} + \boldsymbol{IM} - \boldsymbol{EX}\right)^{-1}\right)\widehat{\boldsymbol{IM}} \qquad (2-13)$$

where $\boldsymbol{M}$ is an $n \times n$ matrix denoting the import ratios, $\boldsymbol{F_{category}}$ are final demand categories, $\boldsymbol{IM}$ are imports, and $\boldsymbol{EX}$ are exports.

2.3.2. Validating the constructed time-series IOTs

Monte Carlo simulations have been applied to Leontief model to analyse uncertainties (Wilting, 2012a). Following this study, the uncertainties in the context of the matrix-based structures of IOTs are analysed through Monte Carlo simulations. The matrix-

[1] Noncompetitive IOTs refer to the IOTs based on noncompetitive imports assumptions, i.e. treating the imported products as different from the domestic ones (Su and Ang, 2013).

base structures of IOTs are unfolded at sector level in terms of total output, total intermediate output, total intermediate input, final demand and value added. Additionally, the uncertainty analysis is conducted based on the following statistical measures. The uncertainty is measured using the 2.5th and 97.5th percentiles of the data (Lu et al., 2011; Pinder et al., 2012; Lauerwald et al., 2015; Su et al., 2015; Ayarzagüena et al., 2020). Also, the 2.5th and 97.5th percentiles of the data represent the lower and upper bounds, respectively. Then, to compare the variations in the uncertainty over time, a Z-score measurement (i.e., a value minus the population mean, divided by the population standard deviation) is also needed. This measurement describes a value's relation to the mean of the data (i.e., a group of values) and is used to compare different datasets.

2.3.3. Calculating CO_2 emissions from multiple perspectives

Direct CO_2 emissions consist of energy- and process-related emissions, which are based on the following equation (Shan et al., 2018).

$$C_{energy} = \sum_r \sum_p C_{rp} = \sum_r \sum_p AD_{rp} \times NCV_r \times EF_r \times O_{rp} \qquad (2-14)$$

where C_{energy} are energy-related emissions, C_{rp} are emissions from sector p consuming fossil fuel r, AD_{rp} means the consumption of fossil fuel r by sector p, NCV_r is net caloric value, EF_r are emission factors, O_{rp} is oxygenation efficiency, $r \in [1,17]$ includes 17 fossil fuel sources, and $p \in [1,47]$ consists of 47 sectors used in the energy statistical system and consistent with those in China's national economic accounting.

Then, process-based emissions are emissions from chemical and physical reactions during the production process. This study only considers cement production, the major contributor to process-based emissions in China (Shan et al., 2019).

$$C_{cement} = AD_{cement} \times EF_{cement} \quad (2-15)$$

where C_{cement} are emissions from cement production, AD_{cement} means the total production of cement, and EF_{cement} is the related emission factor.

Production-, consumption- and income-based emissions are calculated based on IOTs (Meng et al., 2020):

$$\boldsymbol{P_i} = \widehat{\boldsymbol{E}}(\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{F} \quad (2-16)$$

$$\boldsymbol{C_i} = \boldsymbol{E}(\boldsymbol{I} - \boldsymbol{A})^{-1}\widehat{\boldsymbol{F}} \quad (2-17)$$

$$\boldsymbol{I_i} = \widehat{\boldsymbol{VI}}(\boldsymbol{I} - \boldsymbol{H})^{-1}\boldsymbol{E} \quad (2-18)$$

where $\boldsymbol{P_i}$, $\boldsymbol{C_i}$ and $\boldsymbol{I_i}$ are production-, consumption- and income-based emissions of sector i respectively, $\boldsymbol{E}$ represents carbon emissions intensities of sectors, $(\boldsymbol{I} - \boldsymbol{A})^{-1}$ is the Leontief inverse matrix, $(\boldsymbol{I} - \boldsymbol{H})^{-1}$ is the Ghosh inverse matrix, $\boldsymbol{F}$ represents the final demand of sectors, and $\boldsymbol{VI}$ represents the primary inputs (including value added and imports) of sectors.

2.3.4. Identifying CO_2 clusters changes via hierarchical clustering analysis and dynamic programming

Hierarchical clustering is an exploratory tool to identify homogeneous aggregates inside a heterogeneous group (S.-B. Wang et al., 2020), which consists of agglomerative and divisive clustering methods. The former is characterized by a bottom-up fashion by merging the nearest clusters while the latter is about a top-down fashion by splitting large clusters into smaller ones (X. Wang et al., 2016). Here, the agglomerative hierarchical clustering based on the Ward linkage method is applied. Overall, it is to construct a tree where each step in the process is illustrated by a joint of the tree (Liu et al., 2013). The process is explained as follows (Liang et al., 2013): first, each object is separated into a cluster by itself; second, the rule by which objects are separated is relax to link the two most similar clusters; and then, the second step will repeat until all objects are joined in a complete classification tree. In more detail, the initial cluster distances in the Ward's method are defined as the squared Euclidean distance between two clusters (Y.-F. Zhang et al., 2020; Nakhal A et al., 2021):

$$d(a,b) = \sqrt{\sum_i (a_i - b_i)^2} \qquad (2-19)$$

Then, the Ward's method is implemented recursively using the Lance-Williams algorithm to update the cluster distances at each step (Dahal et al., 2014; Y.-F. Zhang et al., 2020; Nakhal A et al., 2021). Specifically, the dissimilarity between the union of two clusters $C_i \cup C_j$ and another cluster C_k is calculated as follows:

$$d(C_i \cup C_j, C_k) = a_i d(C_i, C_k) + a_j d(C_j, C_k) + \beta d(C_i, C_j) \qquad (2-20)$$

$$a_i = \frac{|C_i| + |C_k|}{|C_i| + |C_j| + |C_k|} \qquad (2-21)$$

$$a_j = \frac{|C_j| + |C_k|}{|C_i| + |C_j| + |C_k|} \qquad (2-22)$$

$$\beta = -\frac{|C_k|}{|C_i| + |C_j| + |C_k|} \qquad (2-23)$$

where $d(\cdot)$ represents the distance between two clusters and $|\cdot|$ is the size of each cluster.

The data used are sector-level CO_2 emissions from production, consumption and income perspectives, respectively. The research intervals consist of the last year of every Five-Year Plan (FYP) because the FYP in China has significant impacts on the macro-economy, energy and environment (Lin and Ouyang, 2014; Hu, 2016). CO_2 clusters are clarified into four categories, including low-CO_2 emissions group (cluster 1), medium-low-CO_2 emissions group (cluster 2), medium-high-CO_2 emissions group (cluster 3), high-CO_2 emissions group (cluster 4), so as to reflect the underlying structure present in CO_2 emissions (Fernau and Samson, 1990). Based on CO_2 clusters changes over time, the lock-in, catch-up and unlocking effects of CO_2 clusters could be revealed. Specifically, in this study, the lock-in effect indicates the sector accounting for most CO_2 emissions remains the same over time; the catch-up effect describes the sector changes its position towards higher-CO_2 emissions cluster; and the unlocking effect demonstrates the sector alters its position towards lower-CO_2 emissions cluster.

Subsequently, on the basis of CO_2 clusters changes, a path is referred to as a chain that starts from sector i to ends at sector j through a sequence of other sectors (S. Liang et al., 2015). The strongest path is defined as a particular path that causes the largest CO_2 emissions and possesses the most potentials of CO_2 emissions reduction (Wood, 2009). Then, the strongest path could be figured out by using the idea derived from dynamic programming (DP). DP is a multi-stage decision process based on Bellman's principle which decomposes a control problem to a series of sub-problems (Cai et al., 2009). DP could be flexible in tracking a wide range of systems to be controlled and effective in providing the global optimality while satisfying the system constraints (Li et al., 2012). In doing this, the DP proceeds according to the following steps (Yu et al., 2016a): first, each stage (k) of the control problem is determined as this problem consists of a series of sub-problems; second, the state variables (S_k) are set to describe the state of the system at each stage; third, the decision variables (Z_k) are clarified to represent the decision-making, the contribution function $(D_k(S_k, Z_k))$ is used for providing the value at stage k given the decision variable Z_k from the set Z, and the state transfer equation ($f_k(S_k, Z_k)$) is quantized to depict how the system moves from one state to another; and last, the recursive equation when formulating the optimal value objective function ($Y_k(S)$) is set up as follows.

$$\begin{cases} Y_k(S_k) = \max\limits_{Z_k \in Z}\big(D_k(S_k, Z_k) + Y_{k-1}(S_{k-1})\big) \\ Y_0(S_0) = 0 \end{cases}, k = 1,2,\cdots,T \qquad (2-24)$$

When referring to the idea from DP, this method is applied to all the pairs of vertices representing sectors to incorporate the role of transmission sectors and conduct the inter-sector comparisons for CO_2 emissions from demand and supply sides, with the integrated impacts of sectoral linkages on CO_2 clusters being revealed. Therefore, the strongest paths across time are attained to provide the channels with most potentials of enhancing the efficacy of CO_2 emissions alleviation.

2.3.5. Data

Three main datasets are used in this study: official IOTs, national accounts and CO_2-related data. Official IOTs are in 1997, 2000, 2002, 2005, 2007, 2010, 2012, 2015, 2017, 2018, and 2020, which are from China's National Bureau of Statistics (NBS). National accounts for 1997-2020 are from China's NBS, which include price indices and Gross Domestic Product. CO_2 emissions from 1997 to 2020 are calculated based on energy consumption, cement production and emission factor data. Energy consumption and cement production data are from China's NBS, and emissions factor data are according to (Shan et al., 2018).

2.4. Results and discussion

2.4.1. Time-series IOTs from 1997 to 2020 in China

The time-series IOTs illustrate the economic structure of China from 1997 to 2020.

These series of IOTs were constructed in a uniform format: in the row direction, each IOT consists of an intermediate input-output matrix (42*42), a final demand matrix (42*7), and a total output vector (42*1); in the column direction, besides the same intermediate input-output matrix (42*42), other matrices compose each IOT, including an import matrix (1*49), a value added matrix (4*42), and a total input matrix (1*42). For each IOT, the intermediate input-output matrix represents the intermediate input-outputs among 42 sectors; the final demand matrix is composed of rural household consumption, urban household consumption, government consumption, capital formation, changes in inventories, exports and others; and the value added matrix contains compensation of employees, net taxes on production, depreciation of fixed capital, and operating surplus. Besides, the time-series IOTs are represented at 1997 constant prices and at current prices, respectively.

2.4.2. The validation analyses of time-series IOTs

The uncertainties of time-series IOTs remained low and stable from 1997 to 2020, which is based on the analyses in the context of the matrix-based structures. Overall, the interquartile ranges of Z-scores of sectors became concentrated around zero when the Z-scores of sectors causing the larger uncertainty decreased (Figure 2-1). Meanwhile, the Z-scores of the ranges between upper bounds and lower bounds exhibited positively skewed distributions as the Z-scores of median values were negative (i.e., the median values were less than the mean values) (Figure 2-1). Then, the uncertainties of time-series IOTs are analysed from five aspects, including total output (Figure 2-1a), total intermediate output (Figure 2-1b), total intermediate input (Figure 2-1c), final demand (Figure 2-1d), and value added (Figure 2-1e). At the aggregate level, the uncertainties of time-series IOTs were in the range of [-0.5%, 0.5%] for total output, in the range of [-0.5%, 0.5%] for total intermediate output, in the range of [-0.5%, 0.5%] for total intermediate input, in the range of [-1.1%, 1.2%] for final demand, and in the range of [-1.1%, 1.2%] for value added.

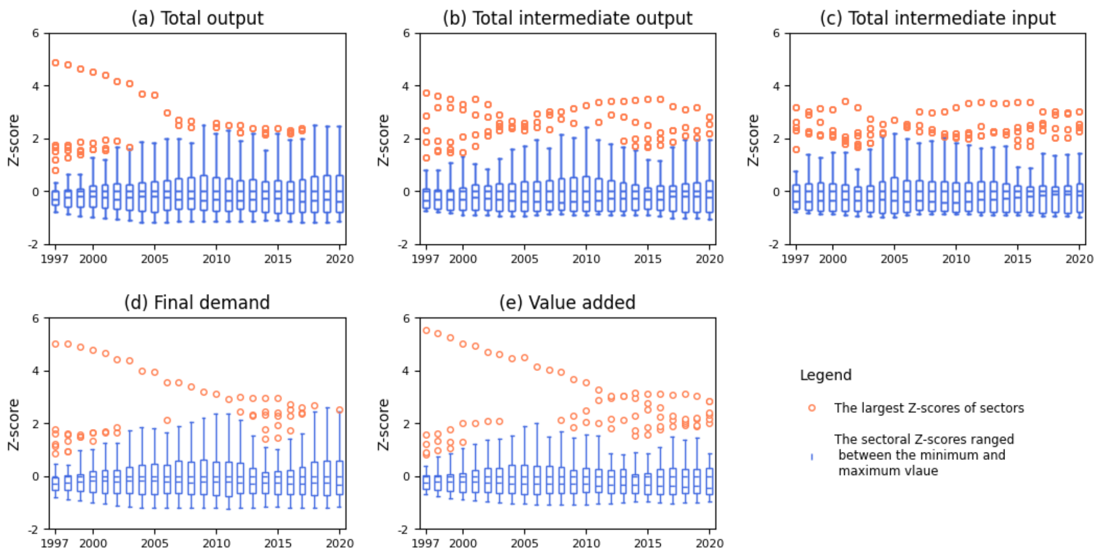

Figure 2-1 Z-scores of the ranges between sectoral upper bounds and sectoral lower bounds of time-series IOTs of China

At the disaggregate level, as far as total output is considered, the sector with the largest uncertainty is changed from *Agriculture* to *Manufacture of Chemicals and Chemical products* to *Construction* which has the Z-scores in the range of [-2.0, 2.1]. As for total intermediate output, the sector accounting for the largest uncertainty is *Manufacture of Chemicals and Chemical Products* that has the Z-scores in the range of [-2.1, 2.1]. In terms of total intermediate input, the sector causing the largest uncertainty is changed from *Manufacture of Chemicals and Chemical Products* to *Construction* with the Z-scores in the range of [-2.0, 2.1]. In light of final demand, the sector occupying the position of the largest uncertainty is changed from *Agriculture* to *Wholesale and Retail Trade* with the Z-scores in the range of [-2.0, 2.0]. With respect to value added, the sector possessing the largest uncertainty is changed from *Agriculture* to *Wholesale and Retail Trade* with the Z-scores in the range of [-2.0, 2.1]. For each element of the intermediate input-outputs, the linkage from *Manufacture of Chemicals and Chemical products* to *Manufacture of Chemicals and Chemical products* has caused the largest uncertainty for most years, with the Z-scores in the range of [-2.1, 2.1]. For each element of final demand, the linkage from *Manufacture of Chemicals and Chemical products* to *Manufacture of Textiles* has accounted for the largest uncertainty for most years, with the Z-scores in the range of [-2.2, 1.9]. For each element of value added, the linkage from *Agriculture* to *Agriculture* has possessed the largest uncertainty, with the Z-scores in the range of [-2.1, 2.1].

2.4.3. CO_2 clusters changes from 1997 to 2020 in China

2.4.3.1. CO_2 emissions from production, consumption and income perspectives

Production-, consumption- and income-based CO_2 emissions provide different thinking in regard to CO_2 emissions reduction in China. In production-based CO_2 emissions (1997-2020), coal use, followed by oil and gas uses, continued generating most emissions (e.g., 76% in 2020) and especially has increased emissions again since 2017 (Figure 2-2a). In consumption-based CO_2 emissions (1997-2020), the composition of emissions was different and changed more obviously: capital formation has kept contributing most to CO_2 emissions (e.g., 49% in 2020); urban household consumption, surpassing exports, became the second largest emitter in 2018 and has continued increasing CO_2 emissions since then (e.g., 20% in 2020) (Figure 2-2b). In the income-based CO_2 emissions from 1997 to 2020, the distribution of emissions was more even: compensation of employees has remained the largest CO_2 emitter (e.g., 33% in 2020); Figure 2-2c shows that depreciation of fixed capital and operating surplus were equally important in generating CO_2 emissions (e.g., 21% and 21% in 2020 respectively). Therefore, the results imply different emissions abatement strategies from the perspectives of production, consumption and income: from the production perspective, reducing the quantity and increase of coal-related emissions is more imperative (Jia and Lin, 2021); from the consumption viewpoint, not only could capital formation be the focus of CO_2 emissions reduction (Gao et al., 2020), but urban household consumption could also be of significance to alleviating CO_2 emissions because of its rapid growth (X.-Y. Liu et al., 2019); and from the income side, simultaneous emissions reduction in compensation of employees, depreciation of fixed capital and operating surplus could be important (Jawad Sajid et al., 2021).

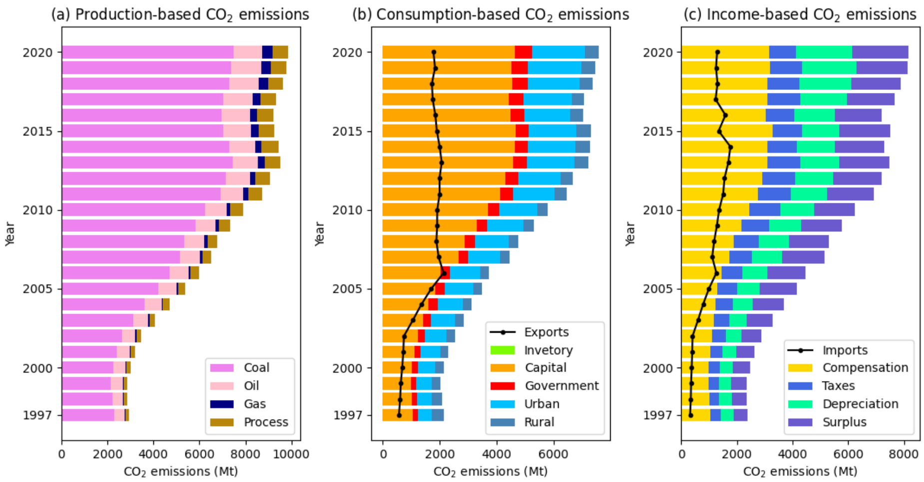

Figure 2-2 CO_2 emissions from production, consumption and income perspectives in China

2.4.3.2. CO_2 clusters from the production, consumption and income perspectives

From the production perspective, sector 23 (*Production and Supply of Electricity and Steam*), sector 12 (*Manufacture of Chemicals and Chemical Products*) and sector 14 (*Manufacture and Processing of Metals*) have composed the two clusters with the higher level of CO_2 emissions since the last year of the 10th FYP (Figure 2-3a). Regarding CO_2 emissions reduction for these sectors, previous studies have explored these sectors' common drivers such as increasing or saturated demand, technological upgrade, industrial structure optimization, energy rebound effects, and difficulties occurred in the non-fossil energy development (Feng et al., 2018; Jiang et al., 2019b, 2020; X. Zhang et al., 2020; Yu et al., 2023). In the meantime, Figure 2-3a shows that these sectors exhibit heterogeneity in energy-related emissions over time. Sector 23 (*Production and Supply of Electricity and Steam*) remained in cluster 4 during the research intervals; sector 12 (*Manufacture of Chemicals and Chemical Products*) and sector 14 (*Manufacture and Processing of Metals*) remained in cluster 3 during the same period; but at the end of the 13th FYP, sector 11 (*Manufacture of Refined Petroleum, Coke Products, Processing of Nuclear Fuel*) has turned out to be one of the members of cluster 2, rather than cluster 1. Correspondingly, there may exist lock-in and catch-up effects in CO_2 emissions (Chen et al., 2011; Z. Liu et al., 2015; H. Wang et al., 2020). Based on these possible effects plus the consideration about the rebound trend of CO_2 emissions in recent years and related key drivers (Y.-X. Zhang et al., 2020), sector-level plans and roadmaps about reducing CO_2 emissions could be characterized by being prominent, targeted and timely (Gielen and Changhong, 2001; X.-Y. Wu et al., 2021), in order to achieve an enhanced balance among the above-mentioned drivers (Chen et al., 2020; Jiang et al., 2019b; X. Zhang et al., 2020). Also, reducing CO_2 emissions could not only focus on upgrades in emitters activities but could also emphasize other economic structure optimization measures, such as developing tertiary industry (C.-S. Zhou et al., 2018) and fostering industries that consume less energy (X.-Q. Zheng et al., 2020).

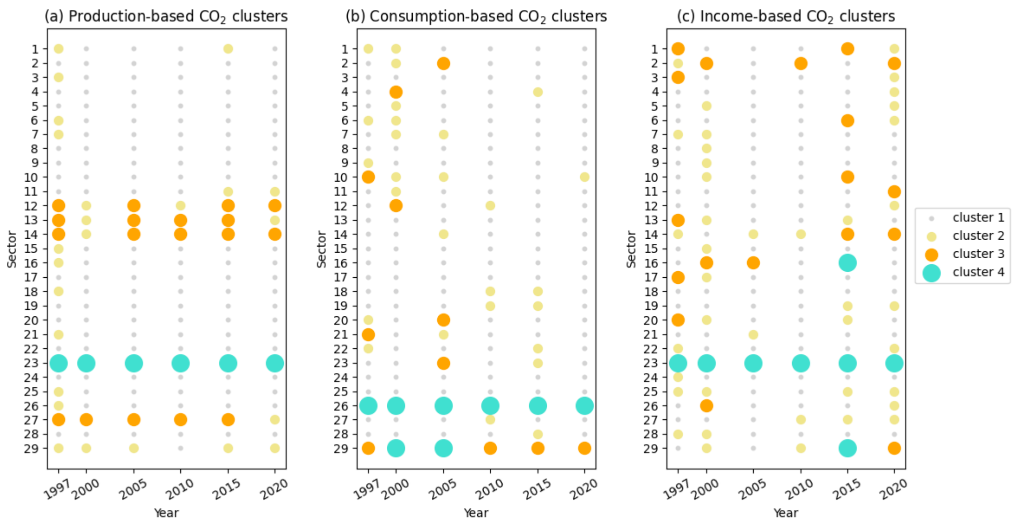

Figure 2-3 Production-, consumption- and income-based CO_2 clusters in China

The general view of CO_2 emissions from consumption perspective shows that the secondary industry still occupied the largest proportion of CO_2 emissions and sector 29 (*Other Services*) also generated large emissions, supporting that economic structural optimization could still be emphasized in mitigating CO_2 emissions from consumption perspective (R.-Z. Wang et al., 2020; Y.-Q. Su et al., 2021). Meanwhile, it is noted that the sectors having generated large consumption-based emissions in the early stage remain the same during the research intervals. Besides, CO_2 clusters have become more concentrated at the end of 11th FYP because the amount of sectors in cluster 2 has experienced the decline when the sectors in clusters 3 and 4 have remain unchanged. These results indicate that there may exist lock-in and unlocking effects in consumption-based CO_2 emissions, which needs special attention during the economic structure optimization (Quadrelli and Peterson, 2007; O' Mahony et al., 2013; Mattauch et al., 2015). Then, similarities and differences in sector-level CO_2 reduction measures from consumption perspective coexist. The consumption viewpoint offers that sector 26 (*Construction*) and sector 29 (*Other Services*) have composed the two clusters with the higher level of CO_2 emissions at the end of 11th FYP (Figure 2-3b). Sector 26 (*Construction*) remained the largest emitter during the research intervals (Figure 2-3b). Promoting low-carbon intermediate inputs, improving the utilization efficiency of intermediate inputs and guiding towards low-carbon final demands could be effective solutions to emissions reduction, which could also be regarded as a general way for emissions reduction from the consumption perspective (Wu et al., 2020). Sector 29 (*Other Services*) remained the second largest emitter during the study period (Figure 2-3b). Financial support and guidelines for technical innovation are advocated, so as to reduce the consumption of electricity, heat and raw materials and to improve energy efficiency (Ge and Lei, 2014).

Based on the results from production and consumption perspectives, the income perspective supports that in CO_2 emissions reduction, the efforts in structure optimization are different but necessary. It is found that some sectors had multiple responsibilities in CO_2 emissions reduction, which indicates that CO_2 emissions reduction could be more effective and efficient when measures proposed from different perspectives for these sectors are considered together. First, the clusters with the higher level of income-based CO_2 emissions have included sector 23 (*Production and Supply of Electricity and Steam*), sector 14 (*Manufacture and Processing of Metals*) and sector

29 (*Other Services*) at the end of 13th FYP (Figure 2-3c). From income perspective, the optimization of economic structure needs complementary measures to reduce CO_2 emissions (Liang et al., 2017; J.-S. Li et al., 2018; H.-R. Zhang et al., 2018; Y.-J. Li et al., 2021). For example, for these identified sectors, suggested measures include controlling land and loan supply, decreasing or cancelling subsidies, increasing revenue taxes, decreasing the depreciation rates of capital used, choosing their downstream users according to income-based CO_2 emissions, and compiling the reports for CO_2 emissions caused by their production and upstream inputs. Also, the utilization of primary resources could be extended in terms of the efficient use of capital (machinery, land and building, etc.), the reallocation of capital and labour resources from high to low carbon-intensive industries, innovation and training (Jawad Sajid et al., 2021; Y.-J. Li et al., 2021). Also, sectors with large income-based CO_2 emissions have been those that have continued generating large income-based CO_2 emissions at the end of 9th FYP when some sectors have changed into the members of cluster 2 (or cluster 3) rather than cluster 1. This indicates that from the income perspective, there may exist lock-in and catch-up effects in CO_2 emissions, which needs special attention during the optimization of economic structure (Quadrelli and Peterson, 2007; O' Mahony et al., 2013; Mattauch et al., 2015). In addition, the identified sectors (including sectors 23 and 14) were also the clusters with the larger amount of CO_2 emissions from the production perspective. Accordingly, CO_2 emissions reduction could be more effective and efficient when measures under different perspectives are considered side by side for these sectors (Tukker et al., 2020; Y.-J. Li et al., 2021).

2.4.3.3. CO_2 clusters from urban household consumption

Indirect CO_2 emissions from urban households (i.e., consumption-based CO_2 emissions driven by urban household consumption, urban HCEs) have been important in total CO_2 emissions. Meanwhile, related CO_2 clusters results support that maintaining and proactively promoting sustainable consumption could be effective to reduce urban

HCEs (Schroeder and Anantharaman, 2017; Shao, 2019). This is particularly crucial because of accelerated urbanisation and the associated socioeconomic changes (e.g., the lifestyle changes) (Y.-M. Li et al., 2015; Apergis and Li, 2016; X.-Y. Liu et al., 2019).

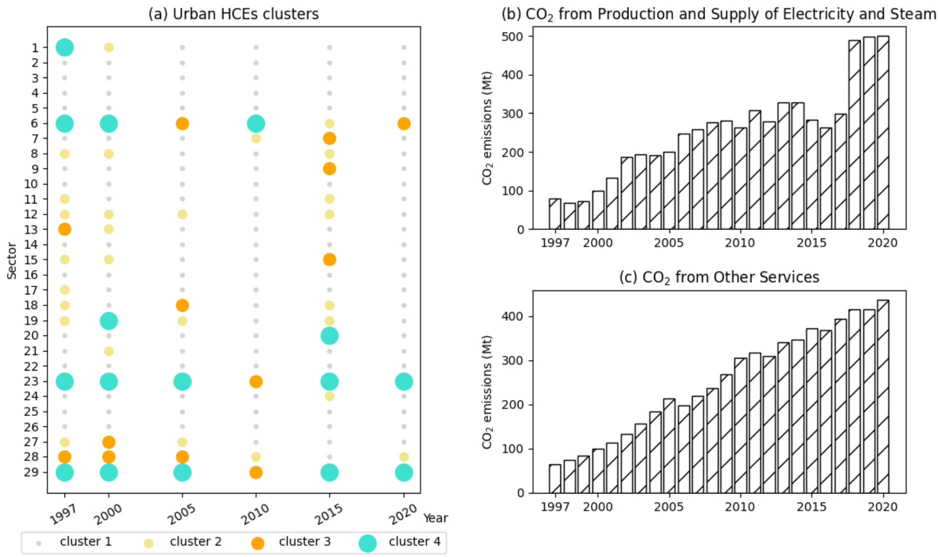

Figure 2-4 Urban HCEs clusters and urban HCEs of specific sectors in China

At the aggregate level, urban households generated the third largest direct CO_2 emissions (e.g., 279.12Mt in 2020), after the secondary industry and sector 27 (*Transport, storage and post*), and have induced the second largest indirect CO_2 emissions since 2018 (e.g., 1814.28Mt in 2020), after capital formation. Moreover, urban households kept generating larger indirect CO_2 emissions than direct CO_2 emissions (e.g., indirect CO_2 emissions were 4 and 6 times more than direct CO_2 emissions in 1997 and 2020 respectively).

At the sector level, fewer sectors in the secondary industry have had the most shares of urban HCEs and these sectors have kept generating large urban HCEs from the early stage. This result indicates that there may exist lock-in effect in urban HCEs. For example, sector 23 (*Production and Supply of Electricity and Steam*), sector 29 (*Other*

Services) and sector 6 (*Manufacture of Food and Tobacco*) composed the two clusters with the higher level of CO_2 emissions at the end of 13th FYP (Figure 2-4a). More especially, sector 23 (*Production and Supply of Electricity and Steam*) and sector 29 (*Other Services*) have remained in cluster 4 for most cases at the research intervals. At the same time, the lock-in effect would be reinforced. It is not only because the amount of CO_2 emissions from the two sectors has remained the largest recently despite the impacts from COVID-19 pandemic (e.g., Figures 2-4b and 2-4c), but also because income growth and urbanization accelerates could bring out the growth in residential electricity consumption (Mi et al., 2020; F. Xu et al., 2021), residential heat demand (Xiong et al., 2015), and high-energy consumption goods and services (Yuan et al., 2015). In these regards, sustainable consumption, simultaneously concentrating on the energy-efficiency of products and the lifestyle and consumer behaviour (W.-L. Liu et al., 2016; Schroeder and Anantharaman, 2017), is advocated to reduce urban HCEs. For example, according to the connotation of sustainable consumption, sector decarbonization needs to be incorporated with rational energy consumption in electricity and heat use. Similarly, in service sectors, the pursuit of lifestyle changes needs to cooperate with the rational conservation of resources and the production and consumption of less energy-intensive goods and services.

2.4.3.4. The strongest paths derived from CO_2 clusters

The strongest paths across time are derived when incorporating the role of transmission sectors and inter-sectoral linkages into CO_2 clusters from demand and supply sides. These paths depict the integrated impacts of sectoral linkages, and provide the channels with most potentials of enhancing the efficacy of CO_2 emissions reduction when applying the general ways which have been explored in Sections 2.4.3.1 to 2.4.3.3 with an aim of reducing CO_2 emissions from production-, consumption- and income-based perspectives (Bai et al., 2018; Jia et al., 2019; Jawad Sajid et al., 2021).

Figure 2-5 shows the strongest paths derived from CO_2 clusters from demand side and related temporal changes. It is noted that sector 23 (*Production and Supply of Electricity and Steam*) remained the starting point of the strongest paths for most of years. This result supports the results of production-based CO_2 clusters, rather than those of consumption-based CO_2 clusters. That means to reduce CO_2 emissions from production- and consumption-based perspectives, it is vital to follow the chains starting from sector 23 (*Production and Supply of Electricity and Steam*), rather than sector 26 (*Construction*). But at the same time, the ending point and the intermediate points of these strongest paths have experienced bigger changes in the research period, during which the inter-sector connections have formulated the different structures of the strongest paths. For example, the strongest path started from the '$S23 \rightarrow S26$' linkage and was completed at the '$S5 \rightarrow S4$' linkage in 1997. But in 2020, the strongest path began at the '$S23 \rightarrow S26$' linkage and was finished at the '$S3 \rightarrow S4$' linkage.

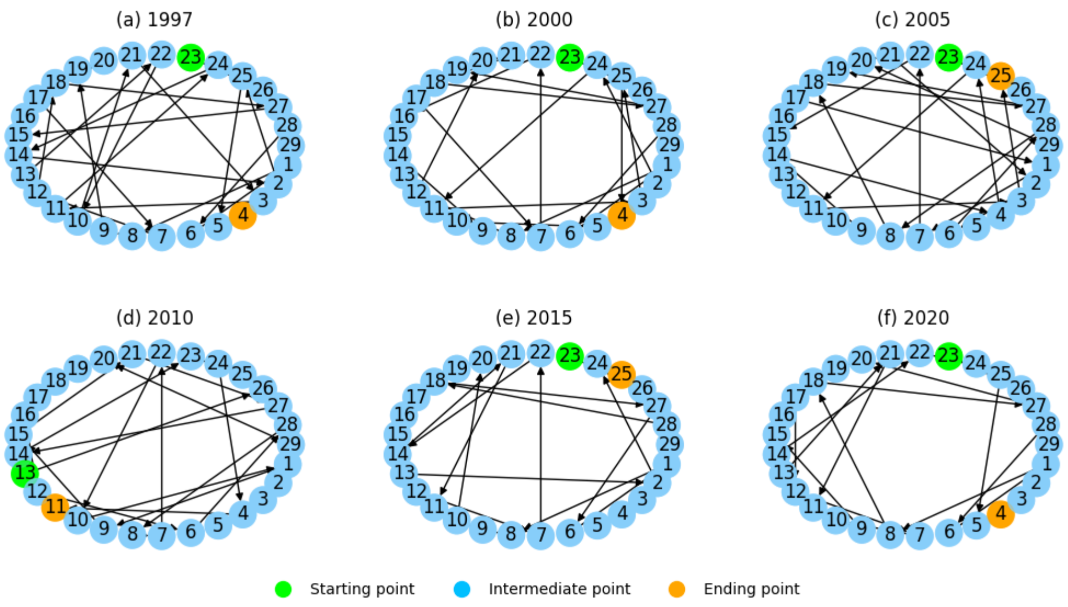

Figure 2-5 The strongest paths derived from CO_2 clusters from demand side

These results indicate that sector 23 (*Production and Supply of Electricity and Steam*) is where to deploy CO_2 emissions reduction efforts first among the inter-sector CO_2 emissions flows regardless of whether the perspective is production- or consumption-based, and it is of necessity to track the strongest paths dynamically due to the temporal changes in the integrated impacts of sector to CO_2 clusters from demand side (Hou et al., 2020; M.-H. Jiang et al., 2021). The former identification also manifests the necessity of constructing a link between the cluster-based carbon abatement and inter-sector linkage-based CO_2 emissions alleviation. These findings could be regarded as the complements to the existing studies (S. Liang et al., 2016; M.-H. Jiang et al., 2021).

Figure 2-6 shows that the strongest paths derived from CO_2 clusters from supply side showed regular patterns over time. In detail, the starting point changed from sector 2 (*Mining and Washing of Coal*) to sector 29 (*Other Services*) at the end of 12th FYP, and the ending point was the same and has remained sector 25 (*Production and Distribution of Water*) since 1997. Regarding more about the inter-sector connections along the strongest paths, the intermediate points showed the temporal changes in the research period. For example, the strongest path started from the '$S2 \rightarrow S23$' linkage and was completed at the '$S8 \rightarrow S25$' linkage in 1997. But in 2020, the strongest path began at the '$S29 \rightarrow S23$' linkage and was finished at the '$S21 \rightarrow S25$' linkage.

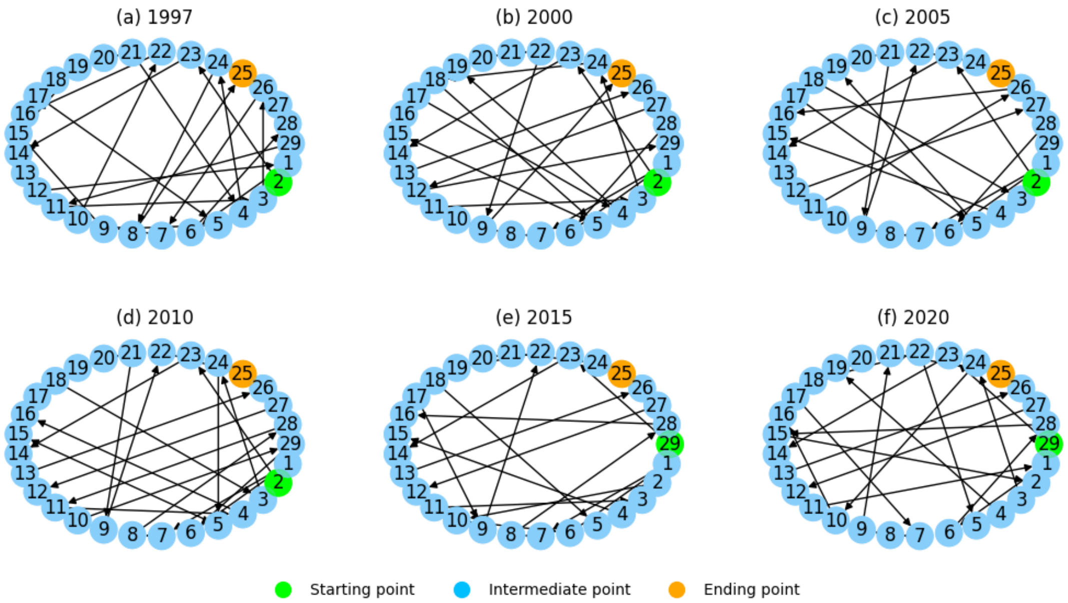

Figure 2-6 The strongest paths derived from CO_2 clusters from supply side

These results indicate the necessity of capturing the strongest paths over time in CO_2 emissions reduction, which is consistent with the findings from demand side. But at the same time, compared with the strongest paths of CO_2 clusters from demand side, the strongest paths from supply side showed the differences in terms of starting point, intermediate points and ending point. This comparison supports tackling CO_2 emissions from supply side needs the specific pathway different from that from demand side, and could also support the applications of supply-side models to CO_2 emissions reduction from the perspective of the strongest paths to extend the existing studies (Zhang, 2010; Liang et al., 2017).

Also, it is noted that in comparison with CO_2 clusters from income perspective, the related strongest paths did not point out the importance of sector 23 (*Production and Supply of Electricity and Steam*) in reducing CO_2 emissions. Instead, the integrated impacts of sector 2 (*Mining and Washing of Coal*) were emphasized until the end of 11th FYP (Figures 2-6a to 2-6d) and then sector 29 (*Other Services*) was regarded as important till the end of 13th FYP (Figures 2-6e to 2-6f). This comparison supports the necessity of constructing a connection between the cluster-based carbon abatement and the inter-sector linkage-based CO_2 emissions alleviation.

Figure 2-7 shows the strongest paths derived from urban HCEs clusters: the starting points of the identified strongest paths remained unchanged at the research intervals, but the ending points and intermediate points of the strongest paths experienced larger changes. For example, sector 23 (*Production and Supply of Electricity and Steam*) kept being the starting points of all the identified strongest paths (Figures 2-7a to 2-7f), which supports the findings of urban HCEs clusters. But in the meantime, the ending points and intermediate points changed with the strongest paths identified (Figures 2-7a to 2-7f), which formulates different structures of the strongest paths. For example, the strongest path started from the '$S23 \rightarrow S6$' linkage and was completed at the '$S21 \rightarrow S3$' linkage in 1997. But in 2020, the strongest path began at the '$S23 \rightarrow S29$'

linkage and was finished at the '$S16 \rightarrow S2$' linkage.

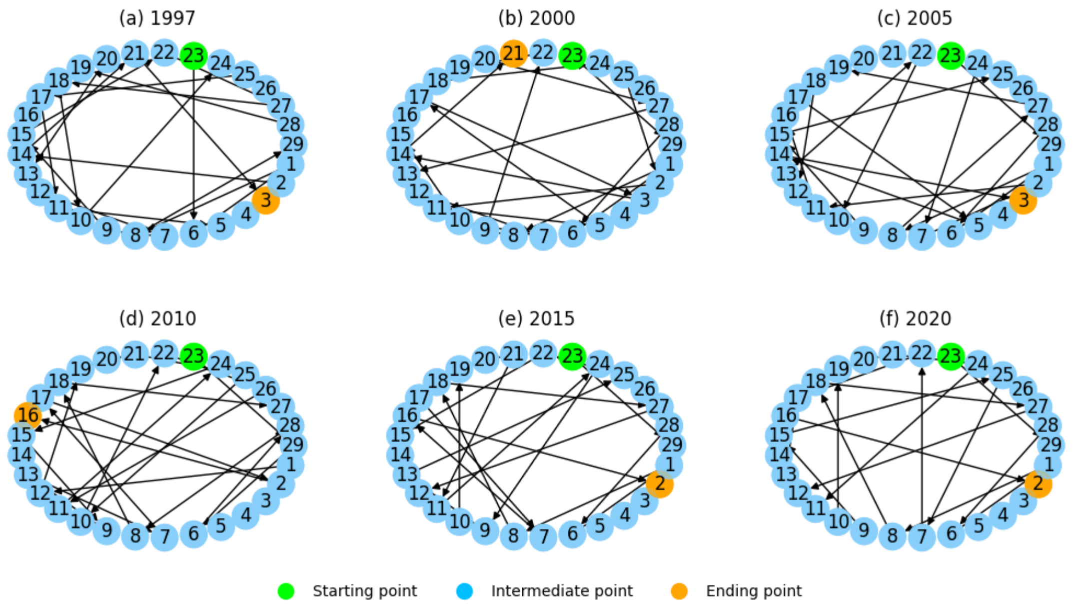

Figure 2-7 The strongest paths derived from urban HCEs clusters

These results provide the channels with most potentials of reducing urban HCEs, which could be conceived as complementary to the studies about HCEs (Fan et al., 2012; Lin et al., 2013; Miao, 2017). Besides, these findings indicate the significance of grasping the strongest paths across time, which supports the necessity of constructing the link between the cluster-based carbon abatement and inter-sector linkage-based CO_2 emissions alleviation, and could find the consistency with the results of the strongest paths derived from CO_2 clusters from demand and supply sides.

2.5. Conclusion

Time-series IOTs elaborate economic structures over time. In this study, we therefore utilize economic structure concerns to updated time-series IOTs. A new matrix calculation method is proposed for tracking and establishing matrix-based links among intermediate input-outputs, final demand and value added. The method is then strengthened by reflecting price fluctuations in IOTs. This method is further extended to capture the structure changes of final demand and value added by proposing a matrix-based linking method. The validation analysis of time-series IOTs is conducted using Monte Carlo simulations in the context of the matrix-based structures of IOTs. This study is in the case of China from 1997 to 2020. Then, the time-series IOTs are constructed in a uniform format, illustrating the economic structures in China from 1997 to 2020. Besides, the time-series IOTs are represented at 1997 constant prices and at current prices, respectively. The uncertainties of time-series IOTs remained low and stable, and the impacts of sectors and linkages on the uncertainties are identified.

Based on the time-series IOTs, changes in CO_2 clusters from production, consumption and income perspectives are identified, deriving and utilizing sector characteristics to reduce CO_2 emissions. First, the role of economic structure optimization is emphasized in CO_2 emissions reduction from production, consumption and income perspectives; meanwhile, during the economic structure optimization, the possible lock-in, catch-up and unlocking effects need attention. Second, to reduce CO_2 emissions, sector-level plans and roadmaps are highlighted from production perspective, sector-level CO_2 emissions reduction measures attaching importance to final demand affecting CO_2 emissions could be feasible from consumption perspective, and the income perspective supports that the measures proposed from multiple perspectives could be considered together for identified sectors besides providing perspective-specific measures. Third, preserving and proactively promoting sustainable consumption is necessary for reducing CO_2 emissions driven by urban household consumption. Last, tracking the strongest paths derived from CO_2 clusters from demand and supply sides could provide the channels with most potentials of enhancing the efficacy of CO_2 emissions reduction.

Chapter 3: A forward-backward realization of solutions to time-series social accounting matrices construction, validation and applications

3.1. Introduction

Social accounting matrix (SAM) is a data accounting system connecting economic activities among economic agents (Defourny and Thorbecke, 1984). It is extensively practical in gauging the impacts of demand and supply (Fernández-Macho et al., 2008) and in building up models for structural and policy analyses (Blancas, 2006). With time-series SAMs, meaningful studies have been conducted. To illustrate, analysing the socio-economic situation of an economy in a historical manner is carried out (Bakker et al., 1994); unveiling the sectoral impacts directly and indirectly over time is achieved (Akkemik, 2012); statistically estimating parameters that characterize the people in artificial economy is fulfilled (Kehoe, 1996); supporting structural change analysis and back-casting/calibration of computable general equilibrium models is accessible (Seventer, 2015); and serving as grounded empirical evidence to contribute to the development of (socio)economic theory is achievable (Santos, 2006).

However, updating time-series SAMs has not been prevalent. Also, when it comes to the solutions to time-series SAMs construction, validation and applications, a forward-backward perspective still deserves attention. The main reason is in relation to an overriding feature of SAM. SAM illustrates a complete flow of economic transactions, that is, from production to factors (including labour and capital) to institutions and then back to production (Bhatt and Munjal, 2013). Within the interlinkages among economic agents, one sector could be the buyer impacting its upstream sectors and it yet could be the supplier influencing its downstream sectors (Lenzen et al., 2019; Zhen and Li, 2021), thereby forming a matrix-based economic structure. In this way, sectoral dependence impacts the entire economy and each sector exerts a two-way impact on other sectors within the context of inter-linkages originating from the strength of demand and supply

(Seung, 2014a; Pedauga et al., 2022; Kebede and Heshmati, 2023): an economic transaction flows forward by sectoral following the distribution chain of outputs to end users while it flows backward through sectoral demanding the inputs from producing sectors (Philippidis et al., 2014). This is what we have termed a forward-backward viewpoint. Against this backdrop, corresponding details are further exploited in the context of time-series SAMs: (1) in the construction procedure, tracking the matrix-based economic structure and harmonizing different accounting systems could be simultaneously important; (2) in the validation procedure, reflecting the economy-wide impact of each element within the matrix-based structure could be a potential attempt; and (3) in the applications procedure, the extensions of multiplier decomposition analysis (MDA) and structural path analysis (SPA) to the supply-driven case could map more in terms of reflecting realities.

Therefore, this study makes efforts to construct, validate and apply time-series SAMs through exploiting the forward-backward features of SAM. In detail, to construct time-series SAMs, a matrix-induced structure is established by modifying matrix transformation technique (MTT) and integrating T-accounts concept. During this construction, K-nearest-neighbour (KNN) algorithm and left-one-out cross-validation (LOOCV) method are combined to handle missing data. To validate time-series SAMs, a new matrix calculation method is proposed to detect the effects of each element on the whole economy. To apply time-series SAMs to CO_2 emissions, demand- and supply-driven cases are analysed and compared by extending MDA and SPA. This study is in the case of China from 1997 to 2020. The remainder of this paper is organized as follows. Section 3.2 provides the literature review. Section 3.3 introduces the methodology and data. Section 3.4 is about results and discussion. Section 3.5 concludes this paper.

3.2. Literature review

3.2.1. SAM construction

SAM could be constructed in a top-down or bottom-up manner. In the former, micro SAM is detailed on the basis of macro SAM (Stuttard and Frogner, 2003), whilst in the latter, data reconciliation methods (e.g., naïve method, RAS which is one bi-proportional matrix balancing technique, and cross entropy) are utilized (Robinson et al., 2001; J. Round, 2003; Temurshoev et al., 2013; Scandizzo and Ferrarese, 2015). Despite the discrepancies between the two manners, there exists a common and illuminating sense, that is, both the coherent relationship between IOT and SAM as well as the potential contributions of T-accounts concept to SAM are of significance during the construction (Pyatt, 1999; J. Round, 2003; J. I. Round, 2003; Lemelin et al., 2013). Following this sense, more details are exploited. IOT is the representation of the economic structure embedded in production activities. Based on IOT, SAM develops into a general equilibrium data system linking economic activities among economic agents (including endogenous and exogenous economic accounts). These two concerns highlight the importance of considering that IOT is not only the main and consistent component of SAM, but IOT itself also needs a detailed construction reflecting its economic structure. Then, when considering the T-accounts, they show the balance between demand and supply for each good or service over a specific accounting period (Pyatt, 1999), and are used to achieve the fundamental characteristic of a double entry accounting system (Ellerman, 1986). Meanwhile, SAM is a double-entry bookkeeping table (Blancas, 2006) which describes an accounting system unravelling the inter-sectoral connections in such a way that, for each account, total income and total expenditure must be the same (Fernández-Macho et al., 2008). This similarity supports the determination of economic accounts included in SAM and the balance of the whole SAM.

In these regards, to construct time-series SAMs, keeping the consistency between time-series IOTs and time-series SAMs, and integrating T-accounts into time-series SAMs are simultaneously important. Regarding time-series IOTs construction, the modified MTT (MMTT) method is used. The features of the MMTT method include: (1) probing into and then establishing a matrix-based economic structure (i.e., matrix-based links among intermediate input-outputs, final demand and value-added); (2) emphasizing economic structure changes over time; (3) adding up in the situation where the final demand signs are inconsistent between the prior table and the target table; (4) making sense regardless of whether the data assumptions are linear or nonlinear; (5) depicting the propagation relationship between Ghosh model and the IOT-related models; and (6) tracing structure changes of final demand and value added through the matrix-based linking method. Then, with time-series IOTs, T-accounts concept is applied to establish the accounts included in time-series SAMs and is also utilized to reconcile time-series IOTs with the established accounts.

Meanwhile, it is also noted that missing data is a phenomenon occurring during time-series SAM construction. Among the methods of handling missing data, KNN algorithm is characterized by straightforward concept, convenient implementation, no requirement for prior knowledge about data distribution, no assumptions on data and missing data mechanisms, and efficient learning from small samples (S.-Y. Liang et al., 2015; Idri et al., 2016; Wang and Wang, 2019; Liao et al., 2020). These characteristics are well-suited to missing data estimation in the context of time-series data. Regarding the influence of the parameter (i.e., the number of selected neighbours) on the KNN algorithm performance, LOOCV is applied to determine the number of neighbours chosen. The advantages of LOOCV include that (1) it is a deterministic procedure (Kocaguneli et al., 2012); (2) it can be sure that the optimum value derived from this method is the absolute optimum value, rather than the local optimum values (Modaresi et al., 2018); and (3) it is an effective validation method for KNN algorithm in the context of small samples (Molinaro et al., 2005; Farahnakian et al., 2013).

3.2.2. SAM validation

There are two constructive ways for SAM validation. One method is useful in exploring the impacts of the row totals and the column totals on a SAM structure (Robinson et al., 2001). But the impact of each element on one SAM is therefore unavailable during this process. The other approach is supportive in introducing the stochastic changes of variables to the validation procedure. But the starting point is from the formalized problem of constrained maximization within the context of generalized cross entropy model (Scandizzo and Ferrarese, 2015; Wang et al., 2015a). Thus, how to reflect the effect of each component on the matrix-based SAM structure could be a consideration in need of attention. It could be noted that, in spite of the differences between IOT and SAM, there also exist similarities between them (Bakker et al., 1994). In detail, the essence of IOT is that industries are connected through the buying and selling of raw materials and that the production structure is conditioned by linkages (Pyatt, 1999). By the same taken, the essence of SAM is concerned with the matrix of transactions and transfers between different institutions (Pyatt, 1999). In this respect, MTT is not constrained to an avenue towards updating time-series IOTs (Wang et al., 2015a) since MTT probes into the economic structure by tracing and establishing matrix-based links, but is considered as a basis to validate SAMs by detecting the matrix-based links within a square matrix.

3.2.3. SAM applications

In the applications of SAMs, it is of necessity to comprehensively understand the impacts from the actual drivers of the economic system. The demand-driven model is used to evaluate the influences originating from final demand because of various measures undertaken affecting the exogenous income levels (Roland-Holst and Sancho, 1995; Acquaye et al., 2017), while the supply-driven model is used to detect the effects starting out from production due to an estimated change in the exogenous costs (Roland-Holst and Sancho, 1995; Fernández-Macho et al., 2008). MDA and SPA, the two widely used methods in the context of SAMs, have been extended from the demand-driven to supply-driven case (Defourny and Thorbecke, 1984; Roland-Holst and Sancho, 1995). MDA is used to capture the effects among and between economic activities within a structure, given an initial injection from exogenous variables (Blancas, 2006). MDA decomposes the total multipliers into four parts including the initial injection effect, the transfer multiplier effect, the open-loop multiplier effect and the closed-loop multiplier effect. SPA is used to explore the effects of paths on the economic system. Different perspectives are applied to study SPA. One viewpoint focuses on the partition of influences between two nodes within an economy into direct, total and global influences, and the other concentrates on tracking the paths through multiple tiers (Defourny and Thorbecke, 1984; Roland-Holst and Sancho, 1995). The latter emphasizes the identification and specification of key paths (Roland-Holst and Sancho, 1995).

When broadening the applications of MDA and SPA, there are some concerns. First, studies tend to compare MDA with SPA to investigate the economy (Defourny and Thorbecke, 1984), because more attention is concentrated on the superiority of one method over the other. However, MDA and SPA could help provide diverse channels for understanding how the economy operates, and, in the field of CO_2 emissions, how to orient the direction of emissions reduction. Second, it is found that the matrix-based arrangements when extending MDA and SPA to the supply-driven case do not give priorities to the convenience of results interpretation (Roland-Holst and Sancho, 1995; Miller and Blair, 2009), because the interpretation of results is inconsistent with the calculation of MDA and SPA in the supply-driven case. Last, in the field of CO_2 emissions, MDA and SPA were usually utilized from the demand-driven perspective, rather than the supply-driven perspective (Lenzen, 2003; Y.-Z. Li et al., 2018). Thus, insights from the latter perspective are not formed (Zhen and Li, 2021).

Based on the previous studies, to construct time-series SAMs, this study uses the MMTT method to track and establish the matrix-based economic structures during IOT construction, and then integrates T-accounts concept to determine accounts and to balance the whole SAM. During this process, KNN algorithm and LOOCV method are combined to tackle missing data. Also, this study renews the mechanism of MTT to carry out SAM validation, with the aim of revealing the impacts of each element within the SAM structure. Subsequently, when extending MDA and SPA to the supply-driven case, the relation of the arrangement already proposed to the one proposed in this study is mathematically detailed. Using the time-series SAMs, this study investigates diverse channels in alleviating demand-driven and supply-driven CO_2 emissions, through extending MDA and SPA. These channels are analysed and compared from the perspectives of multiplier effects, tiers and paths.

3.3. Method and data

3.3.1. Time-series SAMs construction: Integrating MMTT and T-accounts concept

The construction of time-series SAMs goes through two phases. First, time-series IOTs are constructed on the basis of the MMTT method. The procedure of the MMTT method includes: (1) modifying MTT (Wang et al., 2015a) through matrix transposition and applying price indices to construct time-series IOTs at constant prices; (2) combing a matrix-based linking method to update the categories of final demand and value added in IOTs; and (3) constructing the noncompetitive IOTs by introducing technology sources (Su and Ang, 2013).

Matrix transpose is used to modify MTT, which ensures that the modified MTT (MMTT) is still a matrix calculation method emphasizing structural changes and overcomes the three possible weaknesses of MTT (as introduced in Sections 2.1 and 2.2). Through the MMTT method, new matrix-based links among intermediate input-outputs, final demand and value added are tracked and established. Then, price indices are applied directly in the new matrix-based links because MMTT is a matrix calculation method.

In this way, official IOTs (including benchmark and extended IOTs) at constant prices are achieved. Based on the IOTs constructed at constant prices, MMTT, in combination with linear interpolation method, is further applied to construct the IOTs at constant prices in unreported years. Related equations are as follows.

The initial matrix input, $\boldsymbol{X_0}$, is an $(n+1)\times(n+1)$ matrix with elements at current prices:

$$\boldsymbol{X_0} = \begin{bmatrix} \boldsymbol{D_0} & \boldsymbol{F_0} \\ \boldsymbol{V_0} & \boldsymbol{G_0} \end{bmatrix} \qquad (3-1)$$

where $\boldsymbol{D_0}$ is an $n \times n$ matrix depicting intermediate input-outputs among n sectors, $\boldsymbol{F_0}$ represents an $n \times 1$ matrix denoting final demand, $\boldsymbol{V_0}$ is a $1 \times n$ matrix representing sector-level value added, and $\boldsymbol{G_0}$ is the total final demand.

We convert $\boldsymbol{X_0}$ into $\boldsymbol{Y}$ and then transpose $\boldsymbol{Y}$ as follows.

$$\boldsymbol{Y} = \begin{bmatrix} \boldsymbol{d} & \boldsymbol{v} \\ \boldsymbol{f} & \boldsymbol{g} \end{bmatrix} \qquad (3-2)$$

where $\boldsymbol{d} = \left(\widehat{\boldsymbol{V_0}}\right)^{-1}\boldsymbol{D_0}$, $\boldsymbol{v}$ is an $n \times 1$ matrix with each element being one, $\boldsymbol{f} = \left(\widehat{\boldsymbol{G_0}}\right)^{-1}\boldsymbol{F_0}$, $\boldsymbol{g}$ equals one and ^ represents diagonalization of the vector.

$$\boldsymbol{N} = diag\left(1-\sum\nolimits_i^n d_{1i}, 1-\sum\nolimits_i^n d_{2i}, \cdots, 1-\sum\nolimits_i^n d_{ni}\right) + \boldsymbol{d^T} \qquad (3-3)$$

$$\boldsymbol{F_1} = \boldsymbol{NV_1} \qquad (3-4)$$

$$\boldsymbol{D_1} = \widehat{\boldsymbol{V_1}}\boldsymbol{d} \qquad (3-5)$$

$$\boldsymbol{G_1} = \sum \boldsymbol{F_1} \qquad (3-6)$$

where $\boldsymbol{D_1}$, $\boldsymbol{F_1}$, $\boldsymbol{V_1}$ and $\boldsymbol{G_1}$ are the intermediate input-outputs at constant prices, final demand at constant prices, value added at constant prices, and total final demand at constant prices respectively, and $\boldsymbol{d^T}$ means the transpose of the matrix $\boldsymbol{d}$. Correspondingly, $\boldsymbol{X_1}$ represents $\boldsymbol{X_0}$ at constant prices.

$$\boldsymbol{X_1} = \begin{bmatrix} \boldsymbol{D_1} & \boldsymbol{F_1} \\ \boldsymbol{V_1} & \boldsymbol{G_1} \end{bmatrix} \quad (3-7)$$

The MMTT method is further extended to capture the structure changes of final demand and value added by proposing a matrix-based linking method. First, the matrix-based linking method starts from the final demand and value added derived from the results of the MMTT method. Since this linking method is matrix-based, the links between the categories of final demand (or value added) and intermediate input-outputs are established in a direct and deterministic manner. Then, this matrix-based linking method investigates and then establishes the matrix-based structures of final demand (or value added), allowing positive and negative categories of final demand (or value added). Subsequently, the exact temporal impacts of each element of final demand and value added are calculated; meanwhile, the matrix-based structures are consistent with the results from the MMTT method. The characteristics of this matrix-based linking method include achieving automatic and straightforward adjustments when capturing and linking structure changes and reflecting linear and/or non-linear impacts over time. Related equations are as follows.

$$\boldsymbol{U_{category}} = \begin{cases} \widehat{\boldsymbol{u_c}}\widehat{\boldsymbol{U_c}}\boldsymbol{u_n^*}(\widehat{\boldsymbol{u_n}})^{-1} & \boldsymbol{if}\ \ \boldsymbol{u_n} \neq \boldsymbol{0} \\ \widehat{\boldsymbol{u_c}}\boldsymbol{w_m}\boldsymbol{w_n} & \boldsymbol{if}\ \ \boldsymbol{u_n} = \boldsymbol{0} \end{cases} \quad (3-8)$$

$$\boldsymbol{U_c} = \left[\boldsymbol{U_c^p}, \boldsymbol{U_c^n}\right] \quad (3-9)$$

$$\boldsymbol{u_c} = \begin{bmatrix} \boldsymbol{u_p^d} \\ \boldsymbol{u_n^d} \end{bmatrix} \quad (3-10)$$

$$\boldsymbol{w_n} = \begin{bmatrix} \boldsymbol{u_m} \\ \boldsymbol{u_n^*} \end{bmatrix} \qquad (3-11)$$

where $\boldsymbol{U_{category}}$ denote the categories of final demand (or value added) on the basis of the MMTT method and the matrix-based linking method, $\boldsymbol{u_n^*}$ is the vector for the sum of positive and negative values of final demand (or value added) updated by the MMTT method, $\boldsymbol{u_n}$ is the vector for the sum of positive and negative values of final demand (or value added) to update, $\boldsymbol{u_m}$ is the vector for the difference of positive and negative values of final demand (or value added) to update, $\boldsymbol{U_c^p}$ is the vector for the sum of positive values of final demand (or value added) to update, $\boldsymbol{U_c^n}$ is the vector for the sum of negative values of final demand (or value added) to update, $\boldsymbol{u_p^d}$ is the vector for the updated share of each positive final demand (or value added) category in total positive final demand (or value added), $\boldsymbol{u_n^d}$ is the vector for the updated share of each negative final demand (or value added) category in total final demand (or value added), and the new elements added at the end of $\boldsymbol{u_p^d}$ ($\boldsymbol{u_n^d}$) are zeros to form the complete $\boldsymbol{u_p^d}$ ($\boldsymbol{u_n^d}$) when the dimensions of $\boldsymbol{u_p^d}$ and $\boldsymbol{u_n^d}$ are different.

Then, $\boldsymbol{w_m}$ is calculated as follows.

$$\boldsymbol{w_m w_n} = \boldsymbol{w^{-1} w_n} \qquad (3-12)$$

where $\boldsymbol{w}$ is the matrix $\begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}$.

The constructed IOTs need to be converted to noncompetitive IOTs by quantifying the impacts of imports on IOTs. Following the study (Su and Ang, 2013), the impacts of imports are distributed proportionally to the intermediate input-outputs and final demand categories, which is based on the import ratios as follows.

$$\boldsymbol{M} = diag\left(\left(\boldsymbol{D_1} + \boldsymbol{F_{category}} + \boldsymbol{IM} - \boldsymbol{EX}\right)^{-1}\right)\widehat{\boldsymbol{IM}} \qquad (3-13)$$

where $\boldsymbol{M}$ is an $n \times n$ matrix denoting the import ratios, $\boldsymbol{F_{category}}$ are final demand categories, $\boldsymbol{IM}$ are imports, and $\boldsymbol{EX}$ are exports.

Second, on the basis of time-series IOTs, not only is the T-accounts concept applied to establish accounts included in SAMs, but it is also utilized to arrange IOTs and established accounts. In this step, missing data are estimated, which will be described in Section 3.3.2. Consequently, each SAM contains eight blocks including production, factors, institutions, government, the rest of world, investment, inventory, and others. Among these blocks, the production block includes 42 industrial sectors, the factor block includes labour and capital factor accounts, and the institution block includes rural household, urban household and enterprise accounts.

3.3.2. Missing data estimation: Combining KNN with LOOCV

Besides the time-series IOTs, other categories of time-series data are needed to construct time-series SAMs. When using these sorts of data, missing data is an issue to tackle. In this paper, the combination of KNN algorithm with LOOCV is purported. KNN is an instance-based learning algorithm on the basis of the principle that instances in a dataset will generally exist in proximity to other instances having similar properties (Aha et al., 1991; Choudhury and Kosorok, 2020). When extended to the missing data imputation procedure, the KNN algorithm fills in the missing values of an instance based on given k instances close to the one of interest (Jiang and Yang, 2015). LOOCV is a cross-validation method where a single observation is selected from the original sample and used as the validation data while the other observations are used as the training data (Stamoulias and Manolakos, 2013). This procedure is repeated until each observation in the sample is used once as the test data (Chuang et al., 2011). In more detail, the KNN algorithm combined with LOOCV goes through the following phases:

(1) calculating the closeness or similarity between target instance and each instance in the dataset by using Euclidean distance; (2) sorting the calculated closeness or similarities; (3) repeating the procedure of finding the best values of k neighbors according to LOOCV; and (4) calculating the estimation of the target instance based on the determined k instances.

3.3.3. Time-series SAMs validation: Proposing a new matrix calculation method

A new matrix calculation method is proposed to carry out time-series SAMs validation. That is, the mechanism of MTT (Wang et al., 2015a) is renewed when considering the features of the SAM structure. The renewed MTT is further combined with Monte Carlo simulations to conduct uncertainty analysis. As such, four steps are included in this procedure.

First, according to the SAM structure, $\boldsymbol{E}$, an $m \times m$ matrix, consists of the economic transactions (i.e., the expenditure and receipt accounts of m economic actors) within a SAM and is thus expressed as follows.

$$\boldsymbol{E} = \begin{bmatrix} e_{11} & \cdots & e_{1m} \\ \vdots & \ddots & \vdots \\ e_{m1} & \cdots & e_{mm} \end{bmatrix} \qquad (3-14)$$

Second, a matrix for the renewed MTT is constructed as follows.

$$\boldsymbol{D} = \begin{bmatrix} \boldsymbol{C} & \boldsymbol{E_{lm}} \\ \boldsymbol{E_{ml}} & \boldsymbol{U} \end{bmatrix} \qquad (3-15)$$

where $\boldsymbol{D}$ is an $(m+1) \times (m+1)$ matrix, $\boldsymbol{C}$ is an $m \times m$ matrix with each element calculated through dividing the first $(m-1)th$ elements of each row in $\boldsymbol{E}$ by the mth element of that row in $\boldsymbol{E}$, $\boldsymbol{E_{lm}}$ is the mth column vector of $\boldsymbol{E}$, $\boldsymbol{E_{ml}}$ is the mth row vector of $\boldsymbol{E}$, and $\boldsymbol{U}$ equals to zero.

Third, based on the constructed matrix, the matrix-based structure is formed and then applied to Monte Carlo simulations, which is expressed as follows.

$$\boldsymbol{V} = diag(\boldsymbol{C}^{\boldsymbol{MCS}}\boldsymbol{d}) + diag(\boldsymbol{I}) - (\boldsymbol{C}^{\boldsymbol{MCS}})^{\boldsymbol{T}} diag(\boldsymbol{d}) \quad (3-16)$$

$$\boldsymbol{E}_{\boldsymbol{ml}}^{\boldsymbol{MCS}} = \boldsymbol{V}\boldsymbol{E}_{\boldsymbol{lm}}^{\boldsymbol{MCS}} \quad (3-17)$$

$$\boldsymbol{E}_{\boldsymbol{n}}^{\boldsymbol{MCS}} = diag\left(\boldsymbol{E}_{\boldsymbol{lmn}}^{\boldsymbol{MCS}}\right)\boldsymbol{C}_{\boldsymbol{n}}^{\boldsymbol{MCS}} \quad (3-18)$$

$$\boldsymbol{E}^{\boldsymbol{MCS}} = \begin{bmatrix} \boldsymbol{E}_{\boldsymbol{n}}^{\boldsymbol{MCS}} \\ \boldsymbol{E}_{\boldsymbol{ml}}^{\boldsymbol{MCS}} \end{bmatrix} = \begin{bmatrix} e_{11}^{MCS} & \cdots & e_{1m}^{MCS} \\ \vdots & \ddots & \vdots \\ e_{m1}^{MCS} & \cdots & e_{mm}^{MCS} \end{bmatrix} \quad (3-19)$$

where $\boldsymbol{C}^{\boldsymbol{MCS}}$ is $\boldsymbol{C}$ in Monte Carlo simulations, $\boldsymbol{I}$ is the identity vector, $\boldsymbol{d}$ is the identity vector with its mth element equalling to zero, $\boldsymbol{E}_{\boldsymbol{ml}}^{\boldsymbol{MCS}}$ is $\boldsymbol{E}_{\boldsymbol{ml}}$ in Monte Carlo simulations, $\boldsymbol{E}_{\boldsymbol{lm}}^{\boldsymbol{MCS}}$ is $\boldsymbol{E}_{\boldsymbol{lm}}$ in Monte Carlo simulations, $\boldsymbol{E}_{\boldsymbol{lmn}}^{\boldsymbol{MCS}}$ is the matrix derived from the matrix of $\boldsymbol{E}_{\boldsymbol{lm}}^{\boldsymbol{MCS}}$ by including the first $(m-1)$ rows and columns, $\boldsymbol{C}_{\boldsymbol{n}}^{\boldsymbol{MCS}}$ is the matrix derived from the matrix of $\boldsymbol{C}^{\boldsymbol{MCS}}$ by including the first $(m-1)$ elements, $\boldsymbol{E}^{\boldsymbol{MCS}}$ is $\boldsymbol{E}$ in Monte Carlo simulations respectively, and $diag$ represents the diagonalization of a vector.

Last, the uncertainty is measured using the 2.5th and 97.5th percentiles of the data (Lu et al., 2011; Pinder et al., 2012; Lauerwald et al., 2015; Su et al., 2015; Ayarzagüena et al., 2020). Also, the 2.5th and 97.5th percentiles of the data represent the upper and lower bounds, respectively. To compare the variations in the uncertainty over time, a Z-score measurement (i.e., a value minus the population mean, divided by the population standard deviation) is also needed. It is because this measurement describes a value's relation to the mean of the data (i.e., a group of values) and is used to compare different datasets.

3.3.4. Time-series SAM applications: Applied to demand- and supply-driven

cases

3.3.4.1. Accounting multiplier matrices

The accounting multipliers represent the quantitative expressions of the extent where some initial exogenous changes generate effects through the interdependencies associated with endogenous linkage system (Hartono and Resosudarmo, 2008). The accounting multiplier matrix takes a form of a standard inversion of the $(\boldsymbol{I}-\boldsymbol{A})$ matrix in the demand-driven case (Defourny and Thorbecke, 1984; Hartono and Resosudarmo, 2008), written as $\boldsymbol{L}=(\boldsymbol{I}-\boldsymbol{A})^{-1}$ where $\boldsymbol{A}$ refers to the direct input multiplier matrix. In contrast, in the supply-driven case, by extending the Ghosh input-output model (Miller and Blair, 2009), the accounting multiplier matrix is derived from the SAM framework and is thus expressed as $\boldsymbol{G}=(\boldsymbol{I}-\boldsymbol{H})^{-1}$ where $\boldsymbol{H}$ refers to the direct output multiplier matrix (Roland-Holst and Sancho, 1995).

3.3.4.2. Multiplier decomposition analysis (MDA)

To illustrate MDA in the demand-driven and supply-driven cases, the two types of accounting multiplier matrices, which are mentioned in section 3.4.1, could be integrated into a following unified form according to (Pyatt and Round, 2006; Miller and Blair, 2009).

$$\boldsymbol{M}=\begin{bmatrix}\boldsymbol{M_{PP}} & \boldsymbol{0} & \boldsymbol{M_{PI}}\\ \boldsymbol{M_{FP}} & \boldsymbol{0} & \boldsymbol{0}\\ \boldsymbol{0} & \boldsymbol{M_{IF}} & \boldsymbol{M_{II}}\end{bmatrix}=\begin{bmatrix}\boldsymbol{M_{PP}} & \boldsymbol{0} & \boldsymbol{0}\\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0}\\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{M_{II}}\end{bmatrix}+\begin{bmatrix}\boldsymbol{0} & \boldsymbol{0} & \boldsymbol{M_{PI}}\\ \boldsymbol{M_{FP}} & \boldsymbol{0} & \boldsymbol{0}\\ \boldsymbol{0} & \boldsymbol{M_{IF}} & \boldsymbol{0}\end{bmatrix}=\boldsymbol{Q}+\boldsymbol{R}(3-20)$$

where $\boldsymbol{M}$ denotes the matrix of the transaction multipliers among production activities, factors, and institutions ($\boldsymbol{M}$ refers to the direct input multipliers in the demand-driven case while it represents the direct output multipliers in the supply-driven case); $\boldsymbol{Q}$ captures the transfer elements of $\boldsymbol{M}$; $\boldsymbol{R}$ represents the generation of circular flows; $M_{k_ik_j}$ is the element of $\boldsymbol{M}$ mapping the flow from one economic activity (i.e., k_i) to the other economic activity (i.e., k_j); subscript $\boldsymbol{P}$, the representation of productive sectors; subscript $\boldsymbol{I}$, the representation of factors; and subscript $\boldsymbol{F}$, the representation of institutions.

Then, in the demand-driven case, the accounting multipliers are decomposed in the multiplicative and additive manners, respectively (Pyatt and Round, 1979).

$$\boldsymbol{L} = \boldsymbol{L_3 L_2 L_1} \qquad (3-21)$$

$$\boldsymbol{L} = \underbrace{\boldsymbol{I}}_{E_1} + \underbrace{(\boldsymbol{L_1} - \boldsymbol{I})}_{E_2} + \underbrace{(\boldsymbol{L_2} - \boldsymbol{I})\boldsymbol{L_1}}_{E_3} + \underbrace{(\boldsymbol{L_3} - \boldsymbol{I})\boldsymbol{L_2 L_1}}_{E_4} \qquad (3-22)$$

$$\boldsymbol{L_1} = (\boldsymbol{I} - \boldsymbol{Q})^{-\boldsymbol{1}} \qquad (3-23)$$

$$\boldsymbol{L_2} = \left(\boldsymbol{I} + \widetilde{\boldsymbol{C}} + \widetilde{\boldsymbol{C}}^{\boldsymbol{2}}\right) \qquad (3-24)$$

$$\boldsymbol{L_3} = \left(\boldsymbol{I} - \widetilde{\boldsymbol{C}}^{\boldsymbol{3}}\right)^{-\boldsymbol{1}} \qquad (3-25)$$

$$\widetilde{\boldsymbol{C}} = (\boldsymbol{I} - \boldsymbol{Q})^{-\boldsymbol{1}}\boldsymbol{R} \qquad (3-26)$$

where $\boldsymbol{L}$ denotes the matrix of accounting multipliers, $\boldsymbol{L_1}$ represents the transfer multiplier, $\boldsymbol{L_2}$ represents the open-loop or cross multiplier effect, $\boldsymbol{L_3}$ represents the closed-up multiplier effect, $\boldsymbol{E_1}$ is the initial injection effect, $\boldsymbol{E_2}$ is the net contribution of the transfer multiplier effect, $\boldsymbol{E_3}$ is the net contribution of the open-loop or cross multiplier effect, and $\boldsymbol{E_4}$ is the net contribution of the closed-loop multiplier effect.

In supply-driven case, the accounting multipliers are decomposed in the multiplicative and additive manners respectively, based on (Pyatt and Round, 2006; Miller and Blair, 2009).

$$\boldsymbol{G} = \boldsymbol{G_1 G_2 G_3} \qquad (3-27)$$

$$\boldsymbol{G} = \underbrace{\boldsymbol{I}}_{\boldsymbol{N_1}} + \underbrace{(\boldsymbol{G_1} - \boldsymbol{I})}_{\boldsymbol{N_2}} + \underbrace{\boldsymbol{G_1}(\boldsymbol{G_2} - \boldsymbol{I})}_{\boldsymbol{N_3}} + \underbrace{\boldsymbol{G_1}\boldsymbol{G_2}(\boldsymbol{G_3} - \boldsymbol{I})}_{\boldsymbol{N_4}} \tag{3-28}$$

$$\boldsymbol{G_1} = (\boldsymbol{I} - \boldsymbol{Q})^{-1} \tag{3-29}$$

$$\boldsymbol{G_2} = \left(\boldsymbol{I} + \widetilde{\boldsymbol{D}} + \widetilde{\boldsymbol{D}}^2\right) \tag{3-30}$$

$$\boldsymbol{G_3} = \left(\boldsymbol{I} - \widetilde{\boldsymbol{D}}^3\right)^{-1} \tag{3-31}$$

$$\widetilde{\boldsymbol{D}} = \boldsymbol{R}(\boldsymbol{I} - \boldsymbol{Q})^{-1} \tag{3-32}$$

where $\boldsymbol{G}$ denotes the matrix of accounting multipliers, $\boldsymbol{G_1}$ represents the transfer multiplier, $\boldsymbol{G_2}$ represents the open-loop or cross multiplier effect, $\boldsymbol{G_3}$ represents the closed-up multiplier effect, $\boldsymbol{N_1}$ is the initial injection effect, $\boldsymbol{N_2}$ is the net contribution of the transfer multiplier effect, $\boldsymbol{N_3}$ is the net contribution of the open-loop or cross multiplier effect, and $\boldsymbol{N_4}$ is the net contribution of the closed-loop multiplier effect.

Besides, the arrangement proposed in (Roland-Holst and Sancho, 1995) is consistent with the form in demand-driven case. When it comes to its relation to the arrangement used in this study, we explain the relation in terms of the four above-mentioned multiplier effects (Miller and Blair, 2009). First, for the initial injection effect $\boldsymbol{N_1}$, the relation between $\boldsymbol{N_1}$ and $\boldsymbol{E_1}$ is as follows.

$$\boldsymbol{N_1} = \boldsymbol{E_1} = \boldsymbol{I} \tag{3-33}$$

$$\boldsymbol{N_1}^{\boldsymbol{T}} = \boldsymbol{E_1} \tag{3-34}$$

where $\boldsymbol{I}$ is the identity matrix, and the superscript $\boldsymbol{T}$ means the transposition of a matrix.

Second, for the net contribution of the transfer multiplier effect $\boldsymbol{N_2}$, the relation between $\boldsymbol{N_2}$ and $\boldsymbol{E_2}$ is as follows.

$$\boldsymbol{N_2^T} = (\boldsymbol{G_1} - \boldsymbol{I})^{\boldsymbol{T}} = ((\boldsymbol{I} - \boldsymbol{Q})^{-1} - \boldsymbol{I})^{\boldsymbol{T}} = (\boldsymbol{I} - \boldsymbol{Q^T})^{-1} - \boldsymbol{I} = \boldsymbol{E_2} \qquad (3-35)$$

Then, following the second step, the relation between $\boldsymbol{N_3}$ and $\boldsymbol{E_3}$ is as follows.

$$(\boldsymbol{G_1 G_2})^{\boldsymbol{T}} = \boldsymbol{G_2^T G_1^T} \qquad (3-36)$$

$$\boldsymbol{N_3^T} = (\boldsymbol{G_1 G_2} - \boldsymbol{G_1})^{\boldsymbol{T}} = \boldsymbol{E_3} \qquad (3-37)$$

Last, following the third step, the relation between $\boldsymbol{N_4}$ and $\boldsymbol{E_4}$ is as follows.

$$\boldsymbol{N_4^T} = (\boldsymbol{G_1 G_2 G_3} - \boldsymbol{G_1 G_2})^{\boldsymbol{T}} = \boldsymbol{E_4} \qquad (3-38)$$

3.3.4.3. Structural path analysis (SPA)

In the demand-driven case, SPA is evaluated on the basis of the Leontief inverse matrix, $\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{A})^{-1}$. The Leontief inverse matrix is thus expanded by the Taylor series approximation. In this sense, SPA applied to the field of CO_2 emissions is expressed as follows.

$$\boldsymbol{ED} = \boldsymbol{\mu L F} = \boldsymbol{\mu}(\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{F} = \boldsymbol{\mu I F} + \boldsymbol{\mu A F} + \boldsymbol{\mu A^2 F} + \cdots + \boldsymbol{\mu A^n F} \qquad (3-39)$$

where $\boldsymbol{ED}$ denote demand-driven CO_2 emissions, $\boldsymbol{\mu}$ denote CO_2 emissions intensities of economic activities, $\boldsymbol{F}$ denote the exogenous income levels of economic activities, and $\boldsymbol{\mu A^n F}$ denote the contribution of CO_2 emissions from nth tier. Then, assuming i, j, and k are the economic activities at tier 0, tier 1 and tier 3 respectively, the CO_2 emissions of sector i from itself at the zeroth tier is $ED_i^0 = \mu_i F_i$. The CO_2 emissions of the path from sector j at the first tier to sector i is $ED_{ji}^{1\to 0} = \mu_j A_{ji} F_i$. The CO_2

emissions of the path from sector k at the second tier to sector i is $ED_{kji}^{2\to1\to0} = \mu_k A_{kj} A_{ji} F_i$.

In supply-driven case, SPA is evaluated on the basis of the accounting multiplier matrix, $\boldsymbol{G} = (\boldsymbol{I} - \boldsymbol{H})^{-\mathbf{1}}$. Then, SPA applied to the field of CO_2 emissions is expressed as follows.

$$\boldsymbol{ES} = \boldsymbol{VG\mu} = \boldsymbol{V}(\boldsymbol{I} - \boldsymbol{H})^{-\mathbf{1}}\boldsymbol{\mu} = \boldsymbol{VI\mu} + \boldsymbol{VH\mu} + \boldsymbol{VH^2\mu} + \cdots + \boldsymbol{VH^n\mu} \qquad (3-40)$$

where $\boldsymbol{ES}$ denote supply-driven CO_2 emissions, $\boldsymbol{V}$ denote the exogenous costs of economic activities, and $\boldsymbol{VG^n\mu}$ denote the contribution of CO_2 emissions from nth tier. Then, assuming i, j, and k are the economic activities at tier 0, tier 1 and tier 3 respectively, the CO_2 emissions of sector i from itself at the zeroth tier is $ES_i^0 = V_i\mu_i$. The CO_2 emissions of the path from sector j at the first tier to sector i is $ES_{ji}^{1\to0} = V_j H_{ji} \mu_i$. The CO_2 emissions of the paths from sector k at the second tier to sector i is $ES_{kji}^{2\to1\to0} = V_k H_{kj} H_{ji} \mu_i$. In addition, this interpretation of the influence of one path orients from the expansion of the Taylor series approximation, generating a convenience for the translation of results.

Besides, the number of paths increases exponentially with each tier (Lenzen, 2007; Meng et al., 2015): there are n^t paths in each tier where t is the order of tier and n is the number of economic activities. In practice, a pruning method is usually applied (Lenzen, 2007; Meng et al., 2015; Zhen and Li, 2021): a dynamic tree data structure is constructed by pruning the branches of the tree when the value of input paths is lower than the pruning threshold.

3.3.5. Data

There are five categories of data used for this study. The first category of data for production accounts, factor payments and final demand are from IOTs in 1997, 2000, 2002, 2005, 2007, 2010, 2012, 2015, 2017, 2018 and 2020. These IOTs are available from China's National Bureau of Statistics (NBS). The second category of data for price indices and Gross Domestic Product from 1997 to 2020 are from China's NBS. The third category of data for Balance of Payment Presentation from 1997 to 2020 are from State Administration of Foreign Exchange of China. The four category of data for CO_2-related data including energy consumption and cement production data from China's NBS and emissions factor data according to (Shan et al., 2018). The five category of data for debt revenue and interest payment are from China's NBS.

3.4. Results and Discussion

3.4.1. Time-series SAMs from 1997 to 2020 in China

The time-series SAMs illustrate the economic transactions and transfers among economic agents from 1997 to 2020 in China. These series of SAMs are constructed in a uniform format. Each SAM is a 52*52 square matrix: the 52 economic agents in the row direction are consistent with those in the column direction; meanwhile, the distributive and redistributive processes of transactions flows among these 52 agents are documented. Additionally, the 52 economic agents are categorized into the following blocks: (1) the production block (including 42 industrial sectors); (2) the factor block (including labour factor and capital factor accounts); (3) the institution block (including rural household, urban household and enterprise accounts); (4) the government block; (5) the rest of world block; (6) the investment block; (7) the inventory block; and (8) the others block. Besides, the time-series SAMs are represented at 1997 constant prices and at current prices, respectively.

3.4.2. Time-series SAMs validation results

The uncertainty level of time-series SAMs remained steady and level from 1997 to 2020, during which the uncertainties of time-series SAMs were in the range of [-0.7%, 0.7%] during 1997-2020. Also, at the aggregate level, Z-score is to measure the stability of time-series SAMs. Figure 3-1a shows that the upper bounds of the uncertainty maintained the Z-scores at around 1.963 and the lower bounds maintained the Z-scores at around -1.958 from 1997 to 2020. At the economic activity level, Z-score is to measure the importance of each economic activity to uncertainties and then to compare the measured importance among economic activities in time series. Figure 3-1b shows that the Z-scores of economic activities have formed a more fixed pattern since 2002. Especially, most of the economic activities maintained the Z-scores in the range of [-1.074, 2.000]. Activities 27 (*Construction*), 47 (*Enterprise account*) and 50 (*Investment account*) have been the group having larger Z-scores in the range of [2.000, 3.700]. Activity 27 has kept the tendency since 1997, activity 47 has maintained the trend since 1998, and activity 50 has sustained the impact since 1999. Activity 46 (*Urban household account*) was the largest contributors to uncertainties with its Z-scores in the range of [3.700, 4.481], and has sustained the most important position since 2017. Additionally, the link between economic activities contributing most to uncertainties changed from the activity 52 (*Others*)→activity 47 (*Enterprise account*) link to the activity 52 (*Others*)→activity 50 (*Investment account*) link in 2008 and the activity 52 (*Others*) → activity 46 (*Urban household account*) link in 2019, with the upper bounds of its uncertainty having had the Z-scores of around 1.967 and the lower bounds having had the Z-scores at around -1.978.

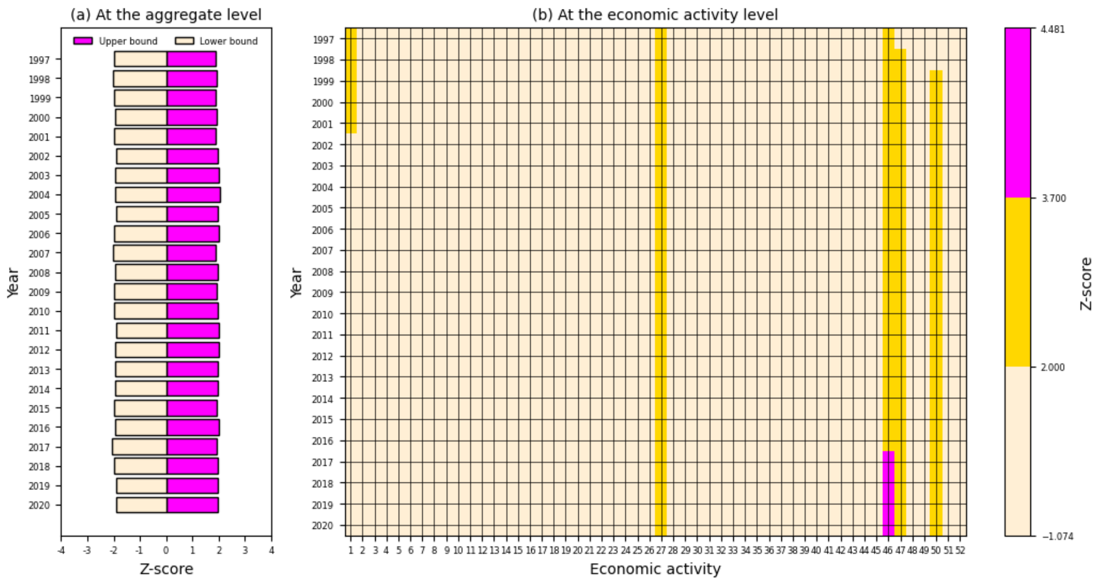

Figure 3-1 Z-scores at the aggregate and economic activity levels

3.4.3. Demand- and supply-driven CO_2 emissions: From multipliers effects

In the demand-driven case, when temporal changes occurred in the exogenous income levels, most impacts on CO_2 emissions tended to be generated through the transfer and closed-loop multiplier effects (Figure 3-2a). In detail, the transfer and closed-loop multiplier effects kept contributing most to emissions (e.g., 68% and 24% respectively in 2020), followed by the open-loop multiplier and initial injection effects (e.g., 4% and 4% respectively in 2020). Moreover, the transfer multiplier effect has decreased its effects on CO_2 emissions from 2015 onwards and its contribution to emissions maintained at about 68%. In contrast, the closed-loop multiplier effect has kept its impacts on CO_2 emissions stable since 2007 and its contributions to emissions reached about 23%, which also indicates there existed potential lock-in effects in the ratio of CO_2 emissions from the closed-loop multiplier effect to total CO_2 emissions. In sum, the results indicate that most of CO_2 emissions continued being generated due to the direct transfers within endogenous accounts, and the completed circular flow of income among endogenous accounts (Defourny and Thorbecke, 1984).

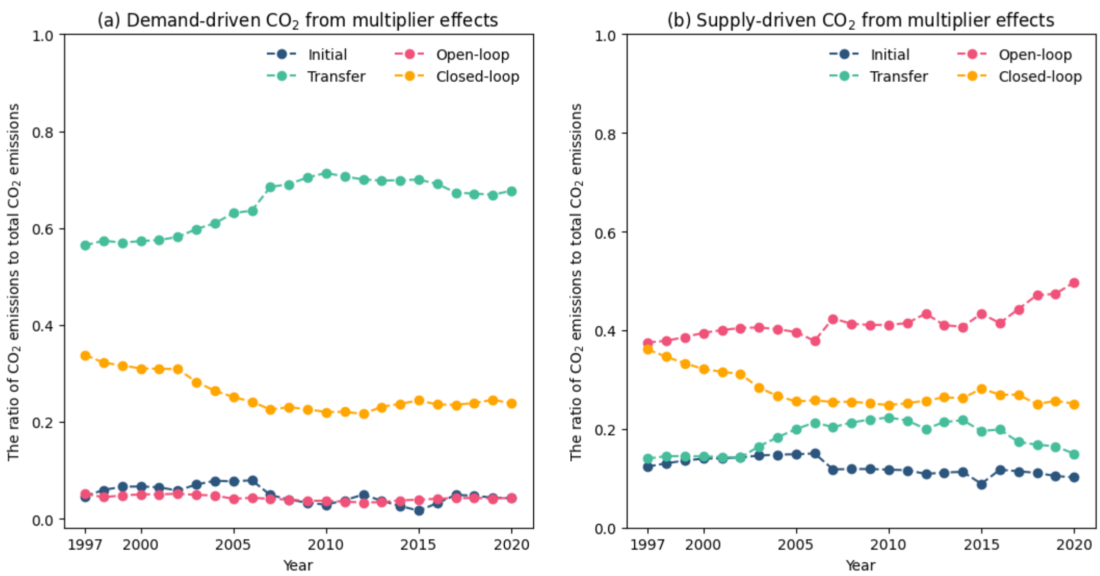

Figure 3-2 Demand- and supply-driven CO_2 emissions from multipliers effects

However, in the supply-driven case, when temporal changes happened to the exogenous costs, most impacts on CO_2 emissions tended to form through the open-loop and closed-loop multiplier effects (Figure 3-2b). Especially, the open-loop and closed-loop multiplier effects contributed most to emissions (e.g., 50% and 25% respectively in 2020), followed by the transfer multiplier and initial injection effects (e.g., 15% and 10% respectively in 2020). Further, the open-loop multiplier effect gradually increased its effects on emissions and its contribution to CO_2 emissions has reached around 47% since 2018. In contrast, the contributions of the closed-loop multiplier effect have fluctuated around 26% since 2005, with potential lock-in effects being noted during this process. These results indicate that most of CO_2 emissions were still from the interactions among and between endogenous accounts, and the impacts exerted on endogenous accounts because of the completed tour through all the endogenous accounts (Roland-Holst and Sancho, 1995).

This comparison emphasizes that, to reduce CO_2 emissions efficiently and effectively, measures could be targeted at different channels (i.e., different types of multipliers effects) (Alcántara et al., 2017) and could be concentrated on tackling the potential lock-in and increasing effects of the targeted channels as well. To illustrate, in the demand-driven case, more attention could be put on reducing the net effects within each endogenous account only (Mondlane et al., 2019), and the within-block net effects arising from the shock after passing from a block, going through net effects from linkages between blocks, coming back to the block (Adelman and Robinson, 1986). On the contrary, in the supply-driven case, increasing attention could be attached to reducing the net effects of linkages between blocks, and the within-block net effects mentioned above (Adelman and Robinson, 1986).

When it comes to the demand-driven multipliers effects at sector level, the structure of each multiplier effect was different from each other during 1997-2020 and the related development modes also differed among multipliers effects (Figure 3-3). In detail, the initial injection effect gradually changed to consist mainly of the shares of sector 27 (*Transportation, Storage and Post*), sector 14 (*Manufacture and Processing of Metals*) and sector 13 (*Manufacture of Nonmetallic Mineral Products*) in CO_2 emissions (Figure 3-3a). The transfer multiplier effect has expanded the impacts from sector 26 (*Construction*), sector 29 (*Other Services*) and sector 16 (*Manufacture of General-Purpose Machinery*) (Figure 3-3b). The open-loop multiplier effect changed the even structure of emissions and were mainly composed of the contributions from sector 33 (*Urban household account*), sector 26 (*Construction*), and sector 29 (*Other Services*) (Figure 3-3c). The closed-loop multiplier effect had experienced the fluctuations before forming a mode where most influences were from sector 26 (*Construction*), sector 29 (*Other Services*) and sector 20 (*Manufacture of Communication Equipment, Computer and Other Electronic Equipment*) (Figure 3-3d). These results indicate that the efficiency and effectiveness of carbon abatement could be further enhanced with the role of specific sectors being dynamically identified in the structure of multipliers effects (Yang et al., 2020), which is a complementary to previous studies when considering the multiplier effect of each sector on CO_2 emissions (J. Liu et al., 2019).

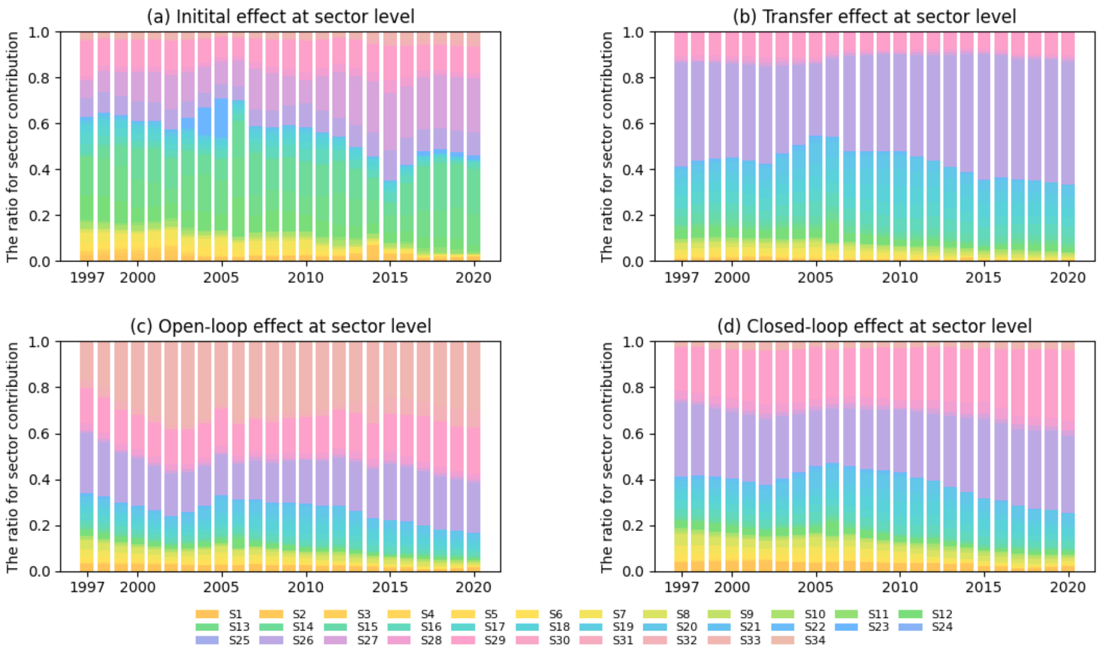

Figure 3-3 Demand-driven multipliers effects at sector level

Regarding the supply-driven multipliers effects at sector level, except the closed-loop effect, other multipliers effects exhibited the stable structures of CO_2 emissions from 1997 to 2020 (Figure 3-4). At the same time, sectoral supply-oriented multipliers effects were different from sectoral demand-oriented multipliers effects during this research period (Figure 3-4). To illustrate, the initial injection effect has continued emphasizing the importance of sector 14 (*Manufacture and Processing of Metals*), sector 23 (*Production and Supply of Electricity and Steam*) and sector 33 (*Urban Household Account*) to CO_2 emissions reduction (Figure 3-4a). The transfer multiplier effect has maintained the level of CO_2 emissions mostly from sector 11 (*Manufacture of Refined Petroleum, Coke Products, Processing of Nuclear Fuel*), sector 14 (*Manufacture and Processing of Metals*), and sector 23 (*Production and Supply of Electricity and Steam*) (Figure 3-4b). The open-loop multiplier effect has consisted mainly of the contributions of sector 34 (*Enterprise Account*), sector 33 (*Urban Household Account*), and sector 32 (*Rural Household Account*) (Figure 3-4c). The closed-loop multiplier effect has been primarily composed of the impacts from sector 34 (*Enterprise Account*), sector 33 (*Urban Household Account*), and sector 29 (*Other Services*) has increased their impacts

(Figure 3-4d). The implications of these results, similar to the results from demand side, could be conceived as the complementary points to previous studies when pointing out the role of typical sectors in reducing CO_2 emissions from supply side (Gallardo and Mardones, 2013). In addition, the specified sectors from supply side provide different hot-spots for CO_2 emissions reduction when compared with those from demand side, which could propel emissions alleviation efforts (Andrés et al., 2021).

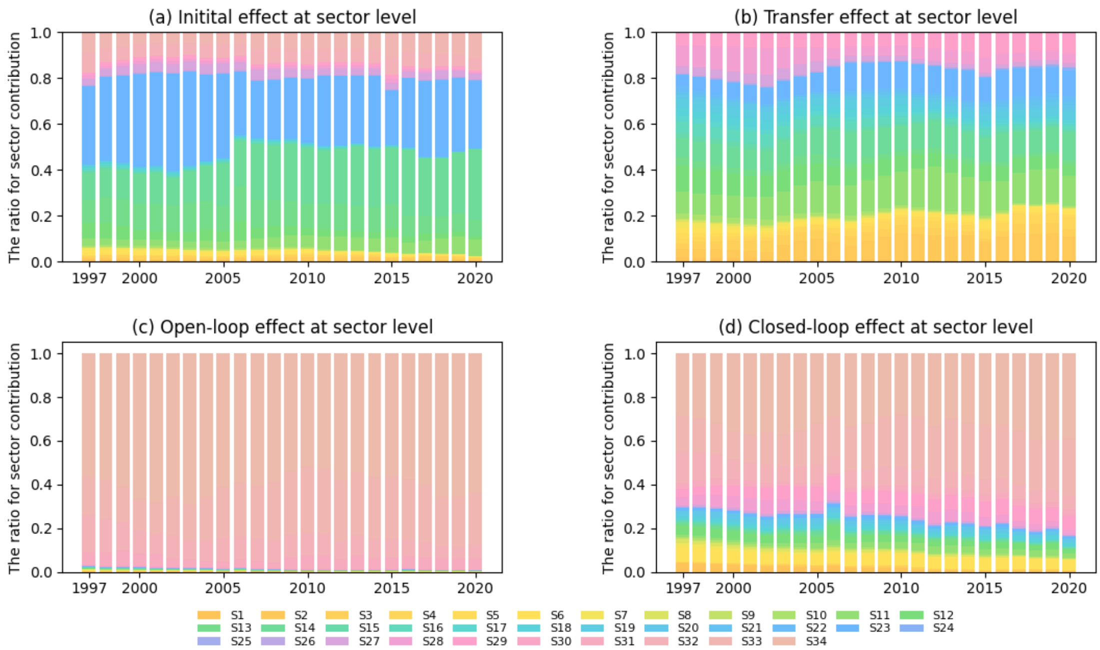

Figure 3-4 Supply-driven multipliers effects at sector level

3.4.4. Demand- and supply-driven CO_2 emissions: From tiers

According to Figure 3-5, the contributions of the first 3 tiers to CO_2 emissions in demand-driven case were different from those in supply-driven case, while it is noted that the first 10 tiers were the main emitters of CO_2 emissions regardless of which case is studied. Moreover, during the period of 1997-2020, the impacts from these tiers were characterized by the potential lock-in and increasing effects (Figure 3-5), which is in common with the impacts from multipliers effects. To illustrate, in the demand-driven case, tiers 1 and 2 exerted the largest effects on CO_2 emissions, accounting for 25% and 19% in 2020 respectively (Figure 3-5a). Besides, regarding the total contributions of the first 10 tiers to CO_2 emissions, after experiencing the fluctuations, the levels since 2015 have shown an overall increasing trend and the level in 2018 reached the peak during 1997-2020 (Figure 3-5a). Conversely, in the supply-driven case, tiers 2 and 3 had the most influences on CO_2 emissions, accounting for 22% and 16% in 2020 respectively (Figure 3-5b). Then, as for the total contributions of the first 10 tiers to CO_2 emissions, after going through the fluctuations, the levels since 2015 have shown an overall increasing trend, and the level in 2018 reached the peak from 1997 to 2020 (Figure 3-5b).

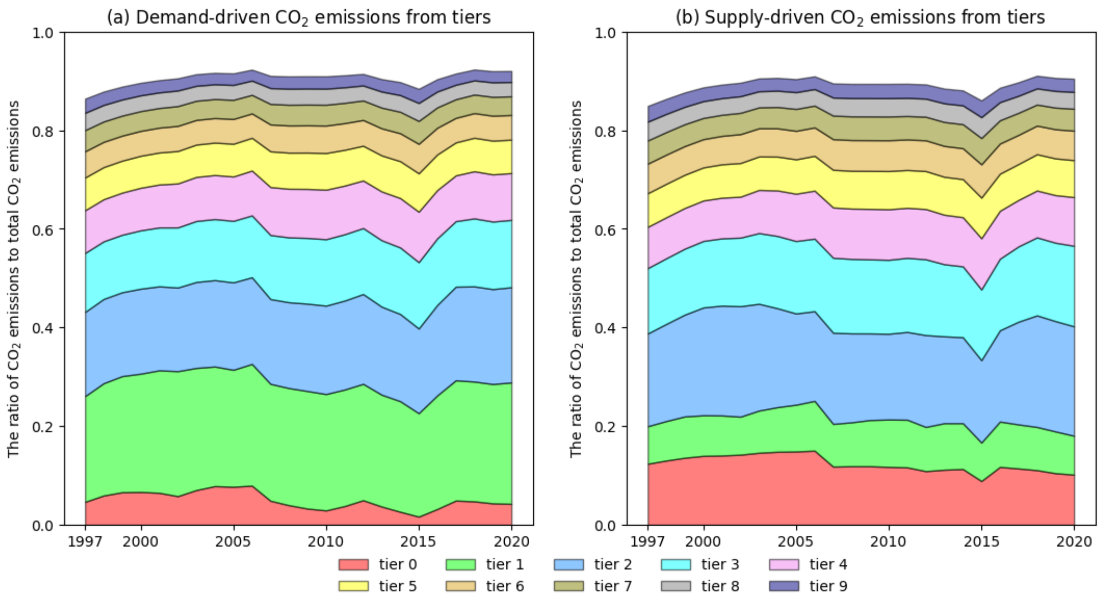

Figure 3-5 Demand- and supply-driven CO_2 emissions from tiers

These results indicate that in the demand- and supply-driven cases, different tiers are expected to be crucial for CO_2 emissions reduction. But in the meantime, the potential lock-in and increasing effects in the contributions of the main tiers to CO_2 emissions are considered as a common issue when reducing CO_2 emissions. In addition, alleviating CO_2 emissions at tier level could be achieved through reducing CO_2 emissions of typical sectors and paths first and then expanding the learned experience to help with tier-level CO_2 emissions alleviation.

As for the tier-level CO_2 emissions across sectors, Figure 3-6 shows the typical tier which is the primary focus of CO_2 emissions reduction for each sector, and its learned experience of carbon abatement could be further extended to other tiers. In detail, for the demand-driven case, tiers 0, 1, 2, 3 and 9 were highlighted across sectors (Figure 3-6a). This result demonstrates that there was the sector heterogeneity in the tier-related results. That is, the aggregate tier-related results discussed before show that tiers 1 and 2 were important to CO_2 emissions reduction while the disaggregate tier-related results indicate that other tiers such as tiers 0 and 9 were also significant for CO_2 emissions reduction. Generally, the most focused tiers are tiers 0, 1 and 2, and from this viewpoint, curbing CO_2 emissions could not be complicated (Wieland and Giljum, 2016; Z. Wang et al., 2018). Additionally, some sectors, such as sectors 13 (*Manufacture of Nonmetallic Mineral Products*), have grasped the stable development mode about CO_2 emissions (Figure 3-6a). On the contrary, other sectors, such as sector 2 (*Mining and Washing of Coal*), have experienced fluctuations (Figure 3-6a). These results indicate there may exist potential lock-in effects in tier-related CO_2 emissions at sector level for some sectors (e.g., sector 13 (*Manufacture of Nonmetallic Mineral Products*)) but tracking the dynamics of tier-related CO_2 emissions is especially important for some sectors (e.g., sector 2 (*Mining and Washing of Coal*)). These findings could not only supplement the aggregate tier-related results, but also complement the previous studies about the disaggregate tier-level results from a temporal perspective (Egilmez et al., 2017) and the expansion of learned experience from the specific tier to other tiers (Wieland and Giljum, 2016).

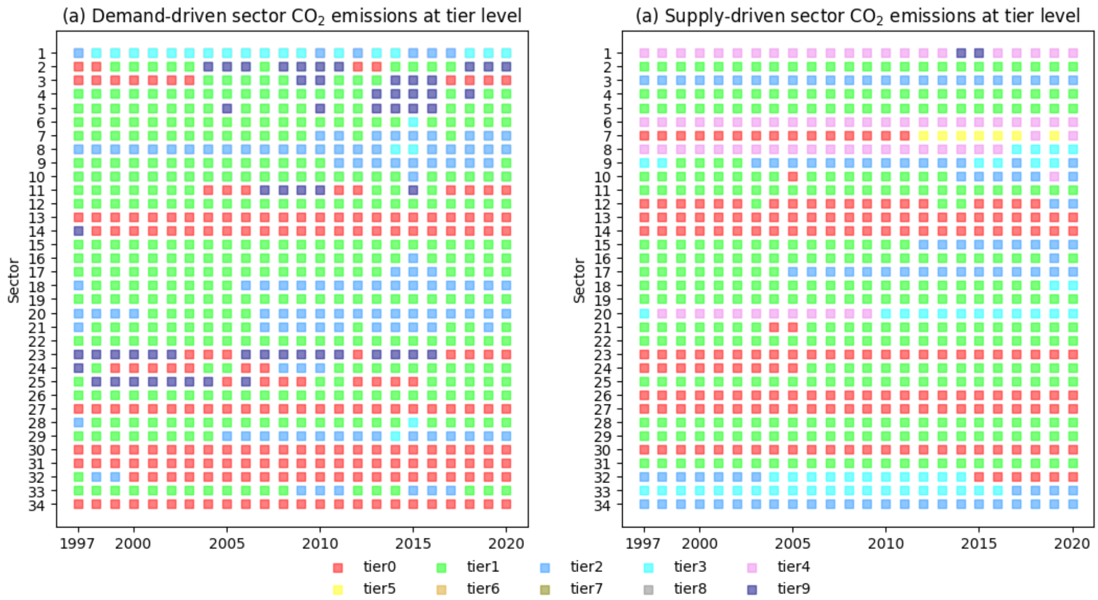

Figure 3-6 Demand- and supply-driven sectoral CO_2 emissions at tier level

Then, for the supply-driven case, compared with the demand-driven case, tier-related CO_2 emissions at sector level show more stable development modes and focus on tiers 0, 1, 2, 3 and 4 (Figure 3-6b). The stable development modes in a general manner indicate that there may exist potential lock-in effects for most of sectors. But at the same time, some sectors, such as sector 7 (*Manufacture of Textiles*), turned out to be the activities where changes in tier-related CO_2 emissions have occurred recently. Besides, the main focuses on specific tiers supplement the aggregate tier-related results discussed before. That is, most of the aggregate tier-related CO_2 emissions were located in tiers 2 and 3 but the tier-related results at sector level suggest tiers 0, 1 and 4 should be considered as crucial for CO_2 emissions alleviation as well. In summary, the results from supply side imply where to curb the tier-level CO_2 emissions from the perspective of sectors, which is a complement for previous studies from demand side (Wieland and Giljum, 2016; Egilmez et al., 2017). Also, the comparison between demand- and supply-driven cases not only provides the common rationale for coping with CO_2 emissions, but it also figures out the specified and different sectors where carbon abatement efforts are supposed to be put into.

3.4.5. Demand- and supply-driven CO_2 emissions: From paths

At the path level, compared with the stable situation in the demand-driven case, the shrinking scope and the increasing influences of CO_2 emissions in the supply-driven case indicate that managing the critical paths in this case could be another way to reduce CO_2 emissions effectively and efficiently (Andrés et al., 2021). In detail, the amount of demand-driven CO_2 emissions paths had experienced fluctuations between 4 and 8 before it has remained level at around 7 since 2012 (Figure 3-7a). In the meantime, the amount of supply-driven CO_2 emissions paths fluctuated between 6 and 9 during 1997-2015 and has decreased from 10 to 8 from 2016 onwards (Figure 3-7b). In addition, the amount in demand-driven case has been mainly smaller than that in supply-driven case since 2003 (Figures 3-7a and 3-7b). Then, the ratio of demand-driven CO_2 emissions from paths increased slowly but that of supply-driven CO_2 emissions from paths showed an increasing trend with fluctuations (Figures 3-7c and 3-7d).

Also, it is noted that the crucial paths and related temporal changes in the demand- and supply-driven cases were different. For instance, the key path in the former case remained activity 13 (*Manufacture of Nonmetallic Mineral Products*) → activity 26 (*Construction*) during the period of 1997-2020, accounting for 7% of total CO_2 emissions. This result reflects that driven by final demand increments, the growth of activity 13 investment led to the increase of investment in activity 26 (Gallardo and Mardones, 2013; J. Liu et al., 2019). This indicates that measures for activity 13, such as improving energy efficiency through high-tech, seeking clean energy alternatives or adjusting industrial structure, could be advocated; meanwhile, measures for activity 26, such as controlling demand and reducing building inventory, could be taken into consideration (Wen and Zhang, 2020). In contrast, the key path in the latter case remained activity 34 (*Enterprise account*) → activity 31 (*Capital factor account*) → activity 23 (*Production and Supply of Electricity and Steam*), the share of its impacts having increased from 6% in 1997 to 7% in 2020. This result means that originated from value added increments, the growth of activity 34 input promoted the increase of activity 31 input, which in turn exerted impacts on the growth of activity 23 (Gallardo and Mardones, 2013; J. Liu et al., 2019). This suggests that measures include controlling supply, decreasing subsidies, increasing revenue taxes, decreasing the depreciation rates of capital used, choosing their downstream users according to income-based CO_2 emissions, and compiling the reports for CO_2 emissions caused by their production and upstream inputs, along with promoting the efficient use of capital (machinery, land and building, etc.), the reallocation of capital and labour resources from high to low carbon-intensive industries, innovation and training (Jawad Sajid et al., 2021; Y.-J. Li et al., 2021).

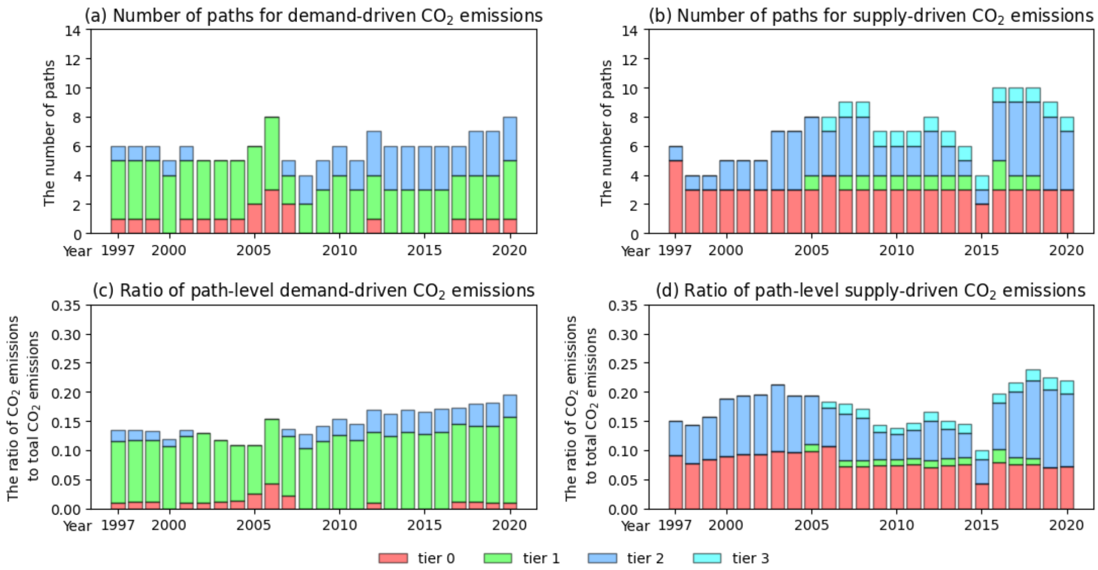

Figure 3-7 Demand- and supply-driven CO_2 emissions in SPA

Besides, even though the tier dimension could help summarize the results of SPA in a general manner and then understand the significance of supply-driven perspective, as shown above, there exist inconsistences between results at tier level (i.e., Section 3.4.4) and those at path level (i.e., this section). For example, tier-level results show that tiers 2 and 3 were important for supply-driven CO_2 emissions reduction while path-level results show that it is tiers 2 and 0 that were significant. This is in common with the demand-driven case. For another example, when CO_2 emissions from higher tiers (e.g., tier 5 and higher tiers) are added up, the necessity of reducing the CO_2 emissions from these tiers increase correspondingly. But this above-mentioned insight is not gained from the results of SPA. However, SPA could serve as a beneficial tool in selecting the typical paths as pilot paths to facilitate CO_2 emissions reduction in diverse aspects such as reducing intermediate purchases or utilizing cleaner alternatives (Shi et al., 2019), further helping with CO_2 emissions reduction at tier level.

3.5. Conclusion

SAM illustrates the economic transactions flowing forward and backward, thereby forming a matrix-based structure. This forward-backward feature of SAM is exploited to help construct, validate and apply time-series SAMs in this study. In detail, to construct time-series SAMs, a matrix-induced structure is established by modifying MTT and integrating T-accounts concept. During this construction, KNN algorithm and LOOCV method are combined to handle missing data in time series. Then, to validate time-series SAMs, a new matrix calculation method is proposed in terms of gauging the economy-wide effect of each element within a matrix-based structure. Also, demand- and supply-driven CO_2 emissions are analysed and compared by extending MDA and SPA. This study is in the case of China from 1997 to 2020.

In this study, time-series SAMs from 1997 to 2020 in China were constructed, each SAM illustrating the economic transactions and transfers among 52 economic agents. Then, through the validation analyses, the uncertainty level of time-series SAMs remained low and level, and the main contributors to uncertainties were identified. Based on time-series SAMs, demand- and supply-driven CO_2 emissions provided different insights at multiplier effect, tier and path levels for CO_2 emissions reduction. In the demand-driven case, more attention could be put on reducing the transfer and closed-loop multiplier effects at the aggregate and sector levels, decreasing the impacts from tiers 1 and 2 with the consideration of sector heterogeneity, and tackling the potential lock-in effects of the crucial paths. On the contrary, in the supply-driven case, more attention could be attached to reducing the closed-loop and open-loop multiplier effects from both the aggregate and sector viewpoints, decreasing the impacts from tiers 2 and 3 with the concern of sector heterogeneity, and tackling the increasing influences of the crucial paths. But there are also common implications derived from these two cases: CO_2 emissions reduction measures could consider the need for coping with the potential lock-in and increasing effects of CO_2 emissions, and selecting the crucial paths as pilot paths to alleviate the CO_2 emissions attributed to different tiers could be a way to reduce CO_2 emissions effectively and efficiently.

Chapter 4: Input-output forecasting and CO_2 inventories construction using a new subsystem decomposition method

4.1. Introduction

Increasing attention could be drawn to forecasting input-output tables and social accounting matrices (hereafter input-output systems in this study). This is because the timeliness of input-output systems has been emphasized in terms of the long time lag of the released table series (Dietzenbacher et al., 2013; Wang et al., 2015b). For example, these table series are very often released every five or more years (Dietzenbacher et al., 2013; Wang et al., 2017). Also, when it comes to exploring the future development of external variables in many fields such as environment (S. Wang et al., 2019), energy (Fan et al., 2007), demography (Cohen and Tuyl, 1991), resources (Jun, 2005), and management (Marangoni and Fezzi, 2002), the input-output systems have provided the analytical frameworks to conduct forecasts and simulations.

However, there are not enough studies to forecast the input-output systems. At the same time, some concerns need to be dealt with during the procedure of input-output forecasting. In detail, some studies relate the RAS method with the combination of macroeconomic data assumptions to the prediction of input-output systems. RAS method is used primarily for balancing an initial estimate (Wang et al., 2015b); meanwhile, macroeconomic data assumptions are affected by stochastic uncertainties (Jiang et al., 2019a). Other studies use the matrix transportation technique (MTT) to probe into and then establish the matrix-based economic structure, in order to predict input-output tables (IOTs) by way of autoregressive integrated moving average (ARIMA) (Zheng et al., 2017). The weaknesses of MTT arise when (1) final demand signs are inconsistent between the prior table and the target table, (2) nonlinear interpolations are considered to reflect temporal changes, and (3) there is a need for depicting the propagation relationship between Ghosh model and the IOT-related models. In the meantime, ARIMA depends on a large amount of data, rather than small samples, so as to complete the predictions of variables (Wang, 2013). ARIMA also requires the mean and variance of response series are independent of time (Y.-W. Wang et al., 2018). Besides, the above-mentioned procedures of input-output forecasting could be extended further in unfolding the forecasts of final demand and value-added and validating the forecasts of input-output systems. In detail, to trace the structure changes of final demand and value added, the exact temporal impacts of each element of final demand and value added needs to be captured and then linked with intermediate input-outputs. Thus, a matrix-based linking method is needed. Also, the validation analysis of time-series input-output systems needs to be conducted in the context of the matrix-based structures of input-output systems, so as to depict the direct and deterministic effects of variables in input-output systems (Zheng et al., 2018).

Regarding one of the applications of the input-output systems forecasts, CO_2 accounting has been conducted to promote carbon abatement (Fan et al., 2007; Zheng et al., 2017). These results facilitate the understanding of the sector-level CO_2 emissions from the consumption-based perspective. But at the same time, it is noted that (1) the sector-level CO_2 emissions are quantified at the aggregate level, without unravelling emissions channels arising from the interdependence among sectors; (2) the sector-level CO_2 accounting completes the static analyses, without considering temporal changes in emissions channels; (3) the sector-level CO_2 emissions could be understood from both consumption- and income-based perspectives within the input-output systems (Zhang, 2010; Cardenete et al., 2012); and (4) the sector-level CO_2 emissions could translate into CO_2 inventories from past to future in order to complement production-based CO_2 inventories in decision-making (Y. Li et al., 2017; B. Zhang et al., 2018).

Therefore, in this study, we propose a procedure of input-output forecasting. During this procedure, the input-output table series are forecasted by means of an element-based Fourier-Markov (EFM) model, then structured through modified matrix transformation technique (MMTT) and T-accounts concept, and last, validated by combining matrix calculation methods with Monte Carlo simulations. On the basis of the forecasted table series, we construct CO_2 inventories by proposing a new integrated method, that is, the combination of subsystem analysis with structural decomposition analysis. With this method, CO_2 inventories quantify historical and future emission channels throughout the economic system from demand and supply sides, and then account for the contributions of influencing factors behind temporal changes in emission channels. This study is in the case of China from 1997 to 2025. The remainder of this study is organized as follows. Section 4.2 reviews the methods for input-output forecasting and CO_2 inventories construction. Section 4.3 introduces methods and data. Section 4.4 is about results and discussion. Section 4.5 concludes this study.

4.2. Literature review

4.2.1. Input-output forecasting

Studies about input-output forecasting could be clarified into two categories. One is concerned with forecasting some external variables (or conducting simulations) by using the benchmark input-output table series as model inputs (Marangoni and Fezzi, 2002; Jun, 2005; Fan et al., 2007; Yu et al., 2016b; S. Wang et al., 2019). The other is about forecasting input-output tables (IOTs) through econometrics method (Zheng et al., 2017), or scenario-based method (Beaufils and Wenz, 2022). During the procedure of input-output forecasting, three aspects are of significance, including: (1) how to forecast the input-output systems; (2) how to structure the forecasted trends of variables within the input-output systems; and (3) how to validate the forecasted input-output systems.

4.2.1.1. Methods of forecasting the input-output systems

To forecast the input-output systems, related studies use RAS method or ARIMA method. The RAS method is used primarily for balancing an initial estimate (Wang et al., 2015b), and further, when RAS is combined with macroeconomic data assumptions, the results to obtain are affected by stochastic uncertainties (Jiang et al., 2019a). The ARIMA model depends on a large amount of data (Wang, 2013), and also requires the mean and variance of response series are independent of time (Y.-W. Wang et al., 2018).

Besides the above-mentioned methods, there are many approaches to predicting external variables (Li et al., 2007; Feng et al., 2012; Zeng et al., 2018), such as regression analysis, time series analysis, grey model, and nonlinear intelligent models. However, regression analysis is limited if there are insufficient data, or if the data are sufficient but not follow certain distribution patterns (Ho, 2010; Belayneh and Adamowski, 2012). Time series analysis requires a large amount of data for forecasting and assumes a linear relationship between the dependent and independent variables while the actual data often present nonlinear relationships (Zhang, 2003; Y.-W. Wang et al., 2018). Grey model could not generate satisfactory predictions when data are nonlinear and has worse curving fitting effects in case of random data (Hsu et al., 2009; R. Wang et al., 2018; Y.-S. Wang et al., 2018). Nonlinear intelligent models depend on a large amount of data; and also these methods need the representativeness of data sets and model interpretability (Pao et al., 2012; J.-D. Wang et al., 2018; Zhao et al., 2022).

The Fourier-Markov model is a mathematical technique for predicting the future values of a time series when the difference between the forecasts from basic models and initial estimates is taken into consideration (Lin et al., 2001; Su et al., 2002). This method has been conceived as a way of enhancing the accuracy of forecasting (Hsu et al., 2009). However, the previous Fourier-Markov method cannot guarantee the accuracy of each observation, cannot ensure the constant good performance when compared with its original model that is based on, and will decrease the scope of application as its current form is not specified in a broad manner. To address these weaknesses, we propose an element-based Fourier-Markov (EFM) method. Also, the EFM method could be applied regardless of whether the amount of data is large or not, which retains the advantages of the Fourier-Markov method (Lin et al., 2001; Su et al., 2002; Hsu et al., 2009).

Besides, the EFM method could be used in the context of short- and long-term forecasting because the conversion matrix in the Markov process and the input parameters of the basic module of Fourier-Markov method could be adjusted according to the changes in future trends (Alfieri et al., 2015; Z. Zhang et al., 2021; Rahnama, 2021). Taking land use as an example, to analyse the future changes of wetlands under the future scenario which is centred on economic construction, the conversion elasticity coefficient of non-wetland increased, and the elasticity coefficients of other wetland types remain unchanged. Correspondingly, the Markov transfer matrix is adjusted, the conversion rate of each wetland type to non-wetland is set to increase by 50%, and the mutual conversion rate of other wetland types is not changed (Z. Zhang et al., 2021). For another example, the basic module of the Fourier-Markov method could proceed with adaptive forecasting that suits the requirements of different planning and future development strategies, which casts its capability of tracking both linear and nonlinear changes in time series data, and its flexibility of directing the future trends when temporal changes occur in practice by means of its model construct (Alfieri et al., 2015).

4.2.1.2. Methods of structuring the forecasts within the input-output systems

The ways of structuring the forecasts differ, depending on the type of the input-output system. In detail, in the context of input-output tables (IOTs), some studies use RAS method to structure the forecasts (Beaufils and Wenz, 2022), and other studies use MTT method to accomplish the structuring (Zheng et al., 2017). The estimates on the basis of RAS method is the outcome of input-output forecasts structuring, but, as mentioned before, RAS is used primarily for balancing an initial estimate. The weaknesses of MTT arise when (1) final demand signs are inconsistent between the prior table and the target table, (2) nonlinear interpolations are considered to reflect temporal changes, and (3) there is a need for depicting the propagation relationship between Ghosh model and the IOT-related models. Except for these concerns, the studies above do not consider the unfolding of final demand and value-added to demonstrate the corresponding categories.

In detail, to trace the structure changes of final demand and value added, the exact temporal impacts of each element of final demand and value added need to be captured, and linked with intermediate input-outputs. The existing methods for updating the categories of final demand and value added are primarily for balancing the initial estimate at the aggregate level and do not emphasize economic structure changes (Huang et al., 2008; Wang et al., 2015a). Hence, a new matrix-based linking method is needed. The characteristics of this new method include achieving automatic and straightforward adjustments when capturing and linking structure changes, and reflecting linear and/or non-linear impacts over time.

In these regards, the MMTT method realizes the following contents, including (1) probing into and then establishing a matrix-based economic structure (i.e., matrix-based links among intermediate input-outputs, final demand and value-added); (2) emphasizing economic structure changes over time; (3) adding up in the situation where the final demand signs are inconsistent between the prior table and the target table; (4) making sense regardless of whether the data assumptions are linear or nonlinear; (5) depicting the propagation relationship between Ghosh model and the IOT-related models; and (6) tracing structure changes of final demand and value added through the matrix-based linking method.

When turning to the context of social accounting matrices (SAMs), current studies do not concentrate on the structuring of input-output forecasts. But the relationships among IOTs, SAMs and T-accounts concept could be supportive in addressing the issue above. Based on IOT, SAM develops into a general equilibrium data system linking economic activities among economic agents (including endogenous and exogenous economic accounts). Then, T-accounts show the balance between demand and supply for each good or service over a specific accounting period (Pyatt, 1999), and are used to achieve the fundamental characteristic of a double entry account system (Ellerman, 1986). In the meantime, SAM is a double-entry bookkeeping table (Blancas, 2006) where it describes an accounting system unravelling the inter-sector connections in such a way that, for each account, total income and total expenditure must be the same (Fernández-Macho et al., 2008). In these regards, MMTT in combination with T-accounts concept could be utilized to complete the structuring of SAMs forecasts.

4.2.1.3. Methods of validating the forecasted input-output systems

Although current studies do not take into consideration the validation of input-output forecasts, the techniques for validating updated IOTs and SAMs have been proposed. In the context of IOTs, matrix similarity indicators are applied to investigate the similarities among IOTs of different versions (Steen-Olsen et al., 2016). Statistical indicators for error estimation are utilized to understand the differences between estimated IOTs and referenced IOTs (Wang et al., 2015b). The Sherman-Morrison-Woodbury formula is applied to the sensitivity analysis by studying the impacts of each direct consumption coefficient (Wilting, 2012a). The matrix perturbation analysis is modified to explore how environmentally extended input-output model is sensitive to the changes of parameters (Mattila et al., 2013). Monte Carlo simulations are applied to Leontief model to investigate uncertainties of IOTs (Wilting, 2012a), which provide more statistical information in relation to the results.

Then, in the context of SAMs, one method explores the impacts of the row totals and the column totals on a SAM structure (Robinson et al., 2001). But the impacts of each element on one SAM are therefore unavailable during this process. The other approach introduces the stochastic changes of variables to the validation procedure. But the starting point is from the formalized problem of constrained maximization within the context of generalized cross entropy model (Scandizzo and Ferrarese, 2015).

In these respects, how to reflect the effects of each element on the matrix-based IOT (or SAM) structure could be a consideration in need of attention. The MMTT method, as mentioned before, probes into and then establishes the matrix-based IOT structure, forming the matrix-based links among intermediate input-outputs, final demand and value-added. Then, on the basis of the properties of a SAM and the characteristics of the MMTT method, a matrix calculation method could be proposed to investigate and then establish the matrix-based SAM structure. Further, with Monte Carlo simulations, these established matrix-based structures could be used to validate the forecasts of the input-output systems.

4.2.2. CO_2 inventories construction

CO_2 inventories are constructed from the production-based perspective, which facilitate the measures of mitigating CO_2 emissions (Shan et al., 2016; Y. Li et al., 2017; Shan et al., 2018). These series of CO_2 inventories, for example, have detailed energy- and process-related emissions (Shan et al., 2018). Further, the production-based CO_2 inventories contributes to developing the baseline, projecting CO_2 emissions, assessing the policy options, and establishing feasible mitigation targets (Y. Li et al., 2017; Chen et al., 2017). Despite the efficacy, the production-based CO_2 inventories do not exhibit the full picture of emissions (B. Zhang et al., 2018). As a supplementary, environmentally-extended input-output models helps investigate the sector-level CO_2 emissions from the consumption- and income-based perspectives, identifying the main targets of CO_2 emissions mitigation measures (Chen et al., 2019). Taken together, there is a need for translating the consumption- and income-based CO_2 emissions at the sector level into the corresponding sector-level CO_2 inventories from past to future, in order to complement the production-based CO_2 inventories in decision-making (Y. Li et al., 2017; B. Zhang et al., 2018).

Considering the characteristics and functions of production-based CO_2 inventories, consumption- or income-based CO_2 inventories could be formed as a detailed decomposition of total emissions. In this sense, subsystem analysis, initially proposed by (Sraffa, 1960), is with respect to the study of a sector or a group of sectors considered as a subsystem interacting with the rest of the sectors (Butnar and Llop, 2011), which helps comprehend the importance of a particular unit to the whole economic system (Alcántara and Padilla, 2009). There are three categories of methods for subsystem analysis. The first approach is utilized to quantify the relations between a specific subsystem and the rest of the whole system, which does not highlight the interconnections induced by each sector (Butnar and Llop, 2011). Although the rest approaches investigate the role of each sector in the whole economic system, they differ in exploring the contributions of the internal and feedback components to the total influences of a specific sector (Sanchez-Choliz, 2003; Alcántara et al., 2017). The idea behind the approach in (Sanchez-Choliz, 2003) is consistent with that from (Alcántara and Padilla, 2009), and also it finds supports in the area of structural path analysis (Lenzen, 2007). But in the meantime, the approach in (Sanchez-Choliz, 2003) has not been applied in the context of the supply-driven model (i.e., Ghosh model). In this regard, the economic system is only explored by demand-driven model (i.e., Leontief model), in which the economy-wide effects arising from final demand, rather than primary inputs, are investigated (Andrés et al., 2021).

Despite the effectiveness of the subsystem analysis in decomposing variables, this analytical method does not evaluate the contributions of influencing factors behind temporal changes in the variables to decompose. To achieve the decomposition of changes, subsystem analysis could be further combined with structural decomposition analysis (SDA). SDA is a decomposition technique related to quantifying both direct and indirect effects of factors on the temporal changes in variables (Zhang, 2010; Cansino et al., 2016). In the field of CO_2 emissions, some studies have extended subsystem analysis by way of SDA, but their studies consider the performance of a group of sectors, rather than sector-specific performance (Butnar and Llop, 2011). In this sense, it is unclear how sector-level CO_2 emissions transmit throughout the economic system. Also, this integrated model is proposed in the demand-driven case, without emphasizing the implications from the supply-driven model. Thus, the decomposition of emissions changes induced by sector-level primary inputs is not informed, thereby decreasing the scope of use in decision-making (Zhang, 2010).

In light of previous studies, we propose a procedure of input-output forecasting. During this procedure, the input-output table series are forecasted by proposing an element-based Fourier-Markov method, then structured through the MMTT method and T-accounts concept, and last, validated by combining matrix calculation methods with Monte Carlo simulations. On the basis of the forecasted table series, we construct CO_2 inventories by proposing a new integrated method, that is, the combination of subsystem analysis with SDA. With this method, CO_2 inventories quantify historical and future emission channels throughout the economic system from both demand and supply sides, and then account for the contributions of influencing factors behind temporal changes in CO_2 emission channels.

4.3. Method and data

4.3.1. Input-output forecasts

To trace the trends inherent in the economic system, the element-based Fourier-Markov (EFM) method is proposed. To explain the EFM method, we start with the modified Fourier correction (MFC) method with basic module. Then, we introduce the Markov process to the MFC method. After that, we evaluate the fitness of EFM method with typical sequences and criteria for the performance evaluation.

4.3.1.1. The MFC method with basic module

The moving average (MA) method is used as the basic module for EFM method because MA method could track both linear and nonlinear changes in time series data (Xiong et al., 2011). The MA method is explained as follows (Hansun, 2013).

$$M_t = M_{t-1} + (y_t - y_{t-n})/n \qquad (4-1)$$

where M_t is the prediction at time t, M_{t-1} is the predicted values at time $t-1$, y_t is the data point value at time t, y_{t-n} is the data point value at time $\mathrm{t}-n$, and n is the number of data points used in the calculation.

Then, the MFC approach is to increase prediction capacity from the considered input data sets. Compared with the previous use of Fourier series, this study proposes four improvements: the first one is using the quotient form of residual series to maintain the consistency between initial estimates and predictions, the second is extending the application of Fourier series to both odd and even cases (Smith, 1999; Selesnick and Schuller, 2000), the third is using the singular value decomposition (SVD) to attain the coefficients of Fourier series, and the fourth is integrating the mechanism where each element gets considered into the Fourier correction. Thus, the MFC method is explained as follows.

$$\boldsymbol{E_r} = \{E_r(1), E_r(2), \cdots, E_r(q)\}^T \qquad (4-2)$$

where E_r is the quotient form of the residuals series, and

$$E_r(k) = y_k/\hat{y}_k, k = 1, 2, \cdots, q \qquad (4-3)$$

Then, the Fourier series can approximate the quotient form of residual series as follows.

$$E_r(k) = \frac{1}{2}a_0 + \sum_{i=1}^{ka}\left[a_i\, cos\left(\frac{i \cdot 2\pi}{T}k\right) + b_i\, sin\left(\frac{i \cdot 2\pi}{T}k\right)\right], k = 1, 2, \cdots, q \qquad (4-4)$$

where $T = q$, and

$$k_a = \begin{cases} \frac{q}{2} + 1, if \ \ q \ \ is \ \ even \\ \frac{(q-1)}{2} + 1, if \ \ q \ \ is \ \ odd \end{cases} \qquad (4-5)$$

The coefficients derived from the Fourier correction approach (i.e., $Q = [a_0, a_1, b_1, a_2, b_2, \cdots, a_{ka}, b_{ka}]^T$), are calculated as follows.

$$\boldsymbol{Q} = \boldsymbol{P}^{\dagger}\boldsymbol{E_r} \qquad (4-6)$$

where $\boldsymbol{P}^{\dagger}$ is the Moore-Penrose pseudo-inverse of $\boldsymbol{P}$ as follows.

$$\boldsymbol{P} = \begin{bmatrix} \frac{1}{2} & cos\left(\frac{2\pi\cdot 2}{T}\right) & sin\left(\frac{2\pi\cdot 2}{T}\right) & cos\left(\frac{2\pi\cdot 2\cdot 2}{T}\right) & sin\left(\frac{2\pi\cdot 2\cdot 2}{T}\right) & \cdots & cos\left(\frac{k_a\cdot 2\pi\cdot 2}{T}\right) & sin\left(\frac{k_a\cdot 2\pi\cdot 2}{T}\right) \\ \frac{1}{2} & cos\left(\frac{2\pi\cdot 3}{T}\right) & sin\left(\frac{2\pi\cdot 3}{T}\right) & cos\left(\frac{2\pi\cdot 2\cdot 3}{T}\right) & sin\left(\frac{2\pi\cdot 2\cdot 3}{T}\right) & \cdots & cos\left(\frac{k_a\cdot 2\pi\cdot 3}{T}\right) & sin\left(\frac{k_a\cdot 2\pi\cdot 3}{T}\right) \\ & & & & \vdots & & & \\ \frac{1}{2} & cos\left(\frac{2\pi\cdot q}{T}\right) & sin\left(\frac{2\pi\cdot q}{T}\right) & cos\left(\frac{2\pi\cdot 2\cdot q}{T}\right) & sin\left(\frac{2\pi\cdot 2\cdot q}{T}\right) & \cdots & cos\left(\frac{k_a\cdot 2\pi\cdot q}{T}\right) & sin\left(\frac{k_a\cdot 2\pi\cdot q}{T}\right) \end{bmatrix} (4-7)$$

The original prediction series can be corrected as follows.

$$\widehat{M_k} = M_k \times E_r(k), k = 1, 2, \cdots, q \qquad (4-8)$$

4.3.1.2. The establishment of EFM method

The MFC method could be adjusted when there are occurred events in future (Lin et al., 2001; Hsu et al., 2009). To achieve this, the Markov process is introduced on the basis of the MFC approach. With this improvement, the new mechanism where the impact of each element on the prediction is integrated into the Fourier-Markov method, the constant good performance when compared with its original model based on is ensured, and the scope of application is complete when its current form is specified in a broad manner. This is what we have termed an element-based Fourier-Markov (EFM) method. The following is the process about how the EFM method operates.

Similar to the MFC method in Section 4.3.1.1, the EFM method uses the quotient form of residual series to maintain the consistency between initial estimates and predictions. The residual errors are portioned into r equal portions called states. Each state is an interval whose width is equal to a fixed portion of the range between the maximum and the minimum of the whole residual error (Li et al., 2007). Let S_j be the jth state.

$$S_j \in [SL_j, SU_j], j = 1, 2, \cdots, r \tag{4-9}$$

where SL_j and SU_j are the lower and upper boundary of the jth state, and r is the integer portion of $ln(n)/\,ln\,2$.

$$SL_{tj} = \min_t e(t) + \frac{j-1}{r}\left(\max_t e(t) - \min_t e(t)\right) \tag{4-10}$$

$$SU_{tj} = \min_t e(t) + \frac{j}{r}\left(\max_t e(t) - \min_t e(t)\right) \tag{4-11}$$

where $e(t)$ is the quotient form of the residual error of the MFC method, $t = 1, 2, \cdots, q$, and $j = 1, 2, \cdots, r$.

Let $P_{ij}^{(m)}$ be the transition probability from the ith state to the jth state by m steps.

$$P_{ij}^{(m)} = \frac{R_{ij}^{(m)}}{R_i}, j = 1, 2, \cdots, r \tag{4-12}$$

where $R_{ij}^{(m)}$ is the transition times that occurred from state i to j by m steps, and R_i is the number of data belonging to the ith state.

Let $Q_t^{(m)} = \left(P_{t1}^{(m)}, P_{t2}^{(m)}, \cdots, P_{tr}^{(m)}\right)$ be the row vector of transition probabilities of ith state at m time steps. The center vector of each state is denoted by $v =$

$\left(v(1), v(2), \cdots, v(r)\right)$, with $v(j) = \sigma \times SL_j + (1-\sigma) \times SU_j$.

The adjusted prediction, $\widehat{M_t^{(a)}}$, in the EFM method is given by

$$\widehat{M_t^{(a)}} = \widehat{M_t} \times Q_t^{(m)} v(j) \qquad (4-13)$$

4.3.1.3. The performance evaluation of EFM method

To demonstrate that the EFM method has the advantages of guaranteeing the accuracy of each observation, ensuring the constant good performance when compared with its original model based on, and enlarging the scope of applications, five typical subsequences and the criteria of evaluating the fitness of MA, MFC and the EFM methods are introduced (Zeng and Li, 2016; Sun et al., 2016). During this process, 10 out of 15 samples are considered as In-Sample for building the architecture of EFM method, and the remaining five samples of each series are considered as Out-of-Sample for evaluating the performance of the forecaster (Zeng and Li, 2016; Saxena, 2021). Then, the five subsequences are explained as follows.

(i). Homogenous exponential sequence

$$Y1: y = 0.8 \times 1.5^q, q = 1,2, \cdots 15$$

(ii). Non-homogenous exponential sequence

$$Y2: y = 1.3 \times 1.8^q + 3.5, q = 1,2, \cdots 15$$

(iii). Approximate non-homogenous exponential sequence

$$Y3: y \approx 1.3 \times 1.4^q + 1.6, q = 1,2, \cdots ,15$$

(iv). Random number sequence including fifteen data points between 40 and 80

$$Y4: y = \begin{pmatrix} 78.3571, 35.0894, 40.8045, 48.9120, 58.0352, \\ 66.4530, 77.8831, 68.2308, 73.0020, 79.3541, \\ 69.4681, 77.5767, 68.9821, 56.9072, 79.7841 \end{pmatrix}$$

(v). Linear function sequence

$$Y5: y = 2.4q + 3.5, q = 1,2,\cdots,15$$

Three criteria are used for evaluating the fitness of MA, MFC and EFM methods: the mean square error (MSE), the absolute mean error (AME), and the mean absolute percentage error (MAPE), which are defined as follows.

$$MSE = \frac{1}{q}\sum_{i=1}^{q}(y_i - \widehat{y_i})^2 \qquad (4-14)$$

$$AME = \frac{1}{q}\sum_{i=1}^{q}|y_i - \widehat{y_i}| \qquad (4-15)$$

$$MAPE = \frac{1}{q}\sum_{i=1}^{q}\left|\frac{y_i - \widehat{y_i}}{y_i}\right| \qquad (4-16)$$

where y_i and $\widehat{y_i}$ are the initial and predicted value of each data point, respectively.

4.3.2. Input-output forecasts structuring

To complete the structuring of input-output forecasts, the process goes through three steps. The first is concerned with proposing MMTT to structure IOTs forecasts. The second is about extending MMTT by a matrix-based linking method to structure the final demand and value-added categories. Last, based on the first two steps, T-accounts concept is applied to structure SAMs forecasts.

Matrix transpose is used to modify MTT, which ensures that the modified MTT (MMTT) is still a matrix calculation method emphasizing structural changes and overcomes the three possible weaknesses of MTT (as introduced in Sections 2.1 and 2.2). Through the MMTT method, new matrix-based links among intermediate input-outputs, final demand and value added are tracked and established. Then, price indices are applied directly in the new matrix-based links because MMTT is a matrix calculation method. In this way, official IOTs (including benchmark and extended IOTs) at constant prices are achieved. Based on the IOTs constructed at constant prices, MMTT, in combination with linear interpolation method, is further applied to construct the IOTs at constant prices in unreported years. Related equations are as follows.

The initial matrix input, $\boldsymbol{X_0}$, is an $(n+1)\times(n+1)$ matrix with elements at current prices:

$$\boldsymbol{X_0} = \begin{bmatrix} \boldsymbol{D}_0 & \boldsymbol{F}_0 \\ \boldsymbol{V}_0 & \boldsymbol{G}_0 \end{bmatrix} \qquad (4-17)$$

where $\boldsymbol{D_0}$ is an $n \times n$ matrix depicting intermediate input-outputs among n sectors, $\boldsymbol{F_0}$ represents an $n \times 1$ matrix denoting final demand, $\boldsymbol{V_0}$ is a $1 \times n$ matrix representing sector-level value added, and $\boldsymbol{G_0}$ is the total final demand.

We convert $\boldsymbol{X_0}$ into $\boldsymbol{Y}$ and then transpose $\boldsymbol{Y}$ as follows.

$$\boldsymbol{Y} = \begin{bmatrix} \boldsymbol{d} & \boldsymbol{v} \\ \boldsymbol{f} & \boldsymbol{g} \end{bmatrix} \qquad (4-18)$$

where $\boldsymbol{d} = \left(\widehat{\boldsymbol{V_0}}\right)^{-1}\boldsymbol{D_0}$, $\boldsymbol{v}$ is an $n \times 1$ matrix with each element being one, $\boldsymbol{f} = \left(\widehat{\boldsymbol{G_0}}\right)^{-1}\boldsymbol{F_0}$, $\boldsymbol{g}$ equals one and ^ represents diagonalization of the vector.

$$\boldsymbol{N} = diag\left(1-\sum\nolimits_i^n d_{1i}\,,1-\sum\nolimits_i^n d_{2i}\,,\cdots,1-\sum\nolimits_i^n d_{ni}\right) + \boldsymbol{d^T} \qquad (4-19)$$

$$\boldsymbol{F_1} = \boldsymbol{NV_1} \tag{4-20}$$

$$\boldsymbol{D_1} = \widehat{\boldsymbol{V_1}}\boldsymbol{d} \tag{4-21}$$

$$\boldsymbol{G_1} = \sum \boldsymbol{F_1} \tag{4-22}$$

where $\boldsymbol{D_1}$, $\boldsymbol{F_1}$, $\boldsymbol{V_1}$ and $\boldsymbol{G_1}$ are the intermediate input-outputs at constant prices, final demand at constant prices, value added at constant prices, and total final demand at constant prices respectively, and $\boldsymbol{d^T}$ means the transpose of the matrix $\boldsymbol{d}$. Correspondingly, $\boldsymbol{X_1}$ represents $\boldsymbol{X_0}$ at constant prices.

$$\boldsymbol{X_1} = \begin{bmatrix} \boldsymbol{D_1} & \boldsymbol{F_1} \\ \boldsymbol{V_1} & \boldsymbol{G_1} \end{bmatrix} \tag{4-23}$$

The MMTT method is further extended to capture the structure changes of final demand and value added by proposing a matrix-based linking method. First, the matrix-based linking method starts from the final demand and value added derived from the results of the MMTT method. Since this linking method is matrix-based, the links between the categories of final demand (or value added) and intermediate input-outputs are established in a direct and deterministic manner. Then, this matrix-based linking method investigates and then establishes the matrix-based structures of final demand (or value added), allowing positive and negative categories of final demand (or value added). Subsequently, the exact temporal impacts of each element of final demand and value added are calculated; meanwhile, the matrix-based structures are consistent with the results from the MMTT method. The characteristics of this matrix-based linking method include achieving automatic and straightforward adjustments when capturing and linking structure changes, and reflecting linear and/or non-linear impacts over time. Related equations are as follows.

$$\boldsymbol{U_{category}} = \begin{cases} \widehat{\boldsymbol{u_c}}\widehat{\boldsymbol{U_c}}\boldsymbol{u_n^*}(\widehat{\boldsymbol{u_n}})^{-1} & \boldsymbol{if} \ \ \boldsymbol{u_n} \neq \boldsymbol{0} \\ \widehat{\boldsymbol{u_c}}\boldsymbol{w_m}\boldsymbol{w_n} & \boldsymbol{if} \ \ \boldsymbol{u_n} = \boldsymbol{0} \end{cases} \quad (4-24)$$

$$\boldsymbol{U_c} = \left[\boldsymbol{U_c^p}, \boldsymbol{U_c^n}\right] \quad (4-25)$$

$$\boldsymbol{u_c} = \begin{bmatrix} \boldsymbol{u_p^d} \\ \boldsymbol{u_n^d} \end{bmatrix} \quad (4-26)$$

$$\boldsymbol{w_n} = \begin{bmatrix} \boldsymbol{u_m} \\ \boldsymbol{u_n^*} \end{bmatrix} \quad (4-27)$$

where $\boldsymbol{U_{category}}$ denote the categories of final demand (or value added) on the basis of the MMTT method and the matrix-based linking method, $\boldsymbol{u_n^*}$ is the vector for the sum of positive and negative values of final demand (or value added) updated by the MMTT method, $\boldsymbol{u_n}$ is the vector for the sum of positive and negative values of final demand (or value added) to update, $\boldsymbol{u_m}$ is the vector for the difference of positive and negative values of final demand (or value added) to update, $\boldsymbol{U_c^p}$ is the vector for the sum of positive values of final demand (or value added) to update, $\boldsymbol{U_c^n}$ is the vector for the sum of negative values of final demand (or value added) to update, $\boldsymbol{u_p^d}$ is the vector for the updated share of each positive final demand (or value added) category in total positive final demand (or value added), $\boldsymbol{u_n^d}$ is the vector for the updated share of each negative final demand (or value added) category in total final demand (or value added), and the new elements added at the end of $\boldsymbol{u_p^d}$ ($\boldsymbol{u_n^d}$) are zeros to form the complete $\boldsymbol{u_p^d}$ ($\boldsymbol{u_n^d}$) when the dimensions of $\boldsymbol{u_p^d}$ and $\boldsymbol{u_n^d}$ are different.

Then, $\boldsymbol{w_m}$ is calculated as follows.

$$\boldsymbol{w_m}\boldsymbol{w_n} = \boldsymbol{w}^{-1}\boldsymbol{w_n} \quad (4-28)$$

where $\boldsymbol{w}$ is the matrix $\begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}$.

The constructed IOTs need to be converted to noncompetitive IOTs by quantifying the impacts of imports on IOTs. Following the study (Su and Ang, 2013), the impacts of imports are distributed proportionally to the intermediate input-outputs and final demand categories, which is based on the import ratios as follows.

$$\boldsymbol{M} = diag\left(\left(\boldsymbol{D_1} + \boldsymbol{F_{category}} + \boldsymbol{IM} - \boldsymbol{EX}\right)^{-1}\right)\widehat{\boldsymbol{IM}} \qquad (4-29)$$

where $\boldsymbol{M}$ is an $n \times n$ matrix denoting the import ratios, $\boldsymbol{F_{category}}$ are final demand categories, $\boldsymbol{IM}$ are imports, and $\boldsymbol{EX}$ are exports.

Except for the forecasted IOTs, the economic accounts included in the SAM framework are forecasted based on the element-based Fourier-Markov (EFM) method, and then using T-accounts concept is to arrange IOTs and forecasted accounts.

4.3.3. Input-output forecasts validation

To validate one forecasted IOT, the process is achieved by the combination of MMTT, which is introduced in section 4.3.2, with Monte Carlo simulations. To validate one forecasted SAM, the process concerning the new matrix calculation method include three steps. First, according to SAM structure, $\boldsymbol{X}$, an $m \times m$ matrix, is composed of the economic transactions (i.e., the expenditure and receipt accounts of m economic agents) within a SAM and is thus expressed as follows.

$$\boldsymbol{X} = \begin{bmatrix} \boldsymbol{x_{11}} & \cdots & \boldsymbol{x_{1m}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{x_{m1}} & \cdots & \boldsymbol{x_{mm}} \end{bmatrix} \qquad (4-30)$$

Second, a matrix for the renewed MTT is constructed as follows.

$$\boldsymbol{Z} = \begin{bmatrix} \boldsymbol{Y} & \boldsymbol{X_{lm}} \\ \boldsymbol{X_{ml}} & \boldsymbol{U} \end{bmatrix} \qquad (4-31)$$

where $\boldsymbol{Z}$ is an $(m+1) \times (m+1)$ matrix, $\boldsymbol{Y}$ is an $m \times m$ matrix with each element calculated through dividing the first $(m-1)th$ elements of each row of $\boldsymbol{X}$ by the mth element of that row of $\boldsymbol{X}$, $\boldsymbol{X_{lm}}$ is the mth column vector of $\boldsymbol{X}$, $\boldsymbol{X_{ml}}$ is the mth row vector of $\boldsymbol{X}$, and $\boldsymbol{U}$ equals to zero.

Third, based on the constructed matrix $\boldsymbol{Z}$, the matrix-based structure is formed and combined with Monte Carlo simulations, which is expressed as follows.

$$\boldsymbol{V} = diag(\boldsymbol{Y^{MCS}d}) + diag(\boldsymbol{I}) - (\boldsymbol{Y^{MCS}})^{\boldsymbol{T}} diag(\boldsymbol{d}) \qquad (4-32)$$

$$\boldsymbol{X_{ml}^{MCS}} = \boldsymbol{V}\boldsymbol{X_{lm}^{MCS}} \qquad (4-33)$$

$$\boldsymbol{X_{n}^{MCS}} = \boldsymbol{diag}\left(\boldsymbol{X_{lmn}^{MCS}}\right)\boldsymbol{Y_{n}^{MCS}} \qquad (4-34)$$

$$\boldsymbol{X^{MCS}} = \begin{bmatrix} \boldsymbol{X_{n}^{MCS}} \\ \boldsymbol{X_{ml}^{MCS}} \end{bmatrix} = \begin{bmatrix} \boldsymbol{x_{11}^{MCS}} & \cdots & \boldsymbol{x_{1m}^{MCS}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{x_{m1}^{MCS}} & \cdots & \boldsymbol{x_{mm}^{MCS}} \end{bmatrix} \qquad (4-35)$$

where $\boldsymbol{Y^{MCS}}$ is $\boldsymbol{Y}$ in Monte Carlo simulations, $\boldsymbol{I}$ is the identity vector, $\boldsymbol{d}$ is the identity vector with its mth element equalling to zero, $\boldsymbol{X_{ml}^{MCS}}$ is $\boldsymbol{X_{ml}}$ in Monte Carlo simulations, $\boldsymbol{X_{lm}^{MCS}}$ is $\boldsymbol{X_{lm}}$ in Monte Carlo simulations, $\boldsymbol{X_{lmn}^{MCS}}$ is the matrix derived from the matrix of $\boldsymbol{X_{lm}^{MCS}}$ by including the first $(m-1)$ rows and columns, $\boldsymbol{Y_{n}^{MCS}}$ is the matrix derived from the matrix of $\boldsymbol{Y^{MCS}}$ by including the first $(m-1)$ elements, $\boldsymbol{X^{MCS}}$ is $\boldsymbol{X}$ in Monte Carlo simulations, and $diag$ represents the diagonalization of a vector.

Then, the uncertainty is measured by using the 2.5th and 97.5th percentiles of the data (Lu et al., 2011; Pinder et al., 2012; Lauerwald et al., 2015; Su et al., 2015; Ayarzagüena et al., 2020), which represent the upper and lower bounds, respectively. To compare the variations in the uncertainty over time, a Z-score measurement (i.e., a value minus the population mean, divided by the population standard deviation) is needed. This measurement describes a value's relation to the mean of the data (i.e., a group of values) and is used to compare different datasets.

4.3.4. A subsystem analysis in demand- and supply-driven contexts

The CO_2 inventories are constructed on the basis of historical and forecasted input-output systems (Cardenete et al., 2012), each system being applied in the contexts of demand-driven and supply-driven models (Zhang, 2010). The demand-driven model records how the production activity pull itself and other sectors to generate emissions, while the supply-driven model shows how the production activity push itself and other sectors to emit emissions (Andrés et al., 2021). In the context of the demand-driven model, to calculate CO_2 emissions, the solution of this input-output system is extended environmentally.

$$\boldsymbol{e} = \boldsymbol{c}(\boldsymbol{I} - \boldsymbol{A})^{-1}\widehat{\boldsymbol{Y}} = \boldsymbol{c}\boldsymbol{L}\widehat{\boldsymbol{Y}} \qquad (4-36)$$

where $\mathbf{e}$ is a $\mathrm{n} \times 1$ vector of total CO_2 emissions, $\mathbf{c}$ is a $1 \times \mathrm{n}$ vector of carbon emission coefficients, $(\boldsymbol{I} - \boldsymbol{A})^{-1}$ (i.e., $\boldsymbol{L}$) is the Leontief inverse matrix, and $\widehat{\boldsymbol{Y}}$ is the diagonalization of final demand vector.

The new subsystem analysis of the environmentally-extended model is explained as follows:

$$\boldsymbol{e_i} = \underbrace{\boldsymbol{c_i y_i}}_{\boldsymbol{DIR_i}} + \underbrace{\boldsymbol{c_i(A_{ii}L_{ii})y_i}}_{\boldsymbol{INT_i}} + \underbrace{\boldsymbol{c_i\left(A_{ij}L_{ji}\right)y_i}}_{\boldsymbol{FEB_i}} + \underbrace{\boldsymbol{c_j L_{ji} y_i}}_{\boldsymbol{SPI_i}} \qquad (4-37)$$

where $\boldsymbol{DIR_i}$ (i.e., the direct component) is the direct CO_2 emissions induced by the final demand of sector i, $\boldsymbol{INT_i}$ (i.e., the internal component) is the CO_2 emissions generated in sector i to produce the inputs which are used by itself to obtain its final demand, $\boldsymbol{FEB_i}$ (i.e., the feedback component) is the CO_2 emissions generated in sector i to obtain the inputs which it sells to other sectors and which these sectors require to obtain the inputs that sector i purchases from them in order to produce its final demand, and $\boldsymbol{SPI_i}$ (i.e., the spillover component) is the CO_2 emissions generated in other sectors to produce the inputs that are used by sector i.

In the context of the supply-driven model, the solution of this environmentally-extended input-output system is as follows.

$$\boldsymbol{k} = \widehat{\boldsymbol{V}}(\boldsymbol{I} - \boldsymbol{H})^{-\boldsymbol{1}}\boldsymbol{c}' = \widehat{\boldsymbol{V}}\boldsymbol{G}\boldsymbol{c}' \qquad (4-38)$$

where $\boldsymbol{k}$ is a $\mathrm{n} \times 1$ vector of total CO_2 emissions, $\widehat{\boldsymbol{V}}$ is the diagonalization of primary inputs, $(\boldsymbol{I} - \boldsymbol{H})^{-\boldsymbol{1}}$ (i.e., $\boldsymbol{G}$) is the Ghosh inverse matrix, and $\boldsymbol{c}'$ is a $\mathrm{n} \times 1$ vector of carbon emission coefficients.

Then, the corresponding new subsystem analysis model is explained as follows:

$$\boldsymbol{k_i} = \underbrace{\boldsymbol{v_i c_i}}_{\boldsymbol{DIR_i}} + \underbrace{\boldsymbol{v_i (H_{ii} G_{ii}) c_i}}_{\boldsymbol{INT_i}} + \underbrace{\boldsymbol{v_i H_{ij} G_{ji} c_i}}_{\boldsymbol{FEB_i}} + \underbrace{\boldsymbol{v_i G_{ij} c_j}}_{\boldsymbol{SPI_i}} \qquad (4-39)$$

where $\boldsymbol{DIR_i}$ (i.e., the direct component) is the direct CO_2 emissions induced by the primary inputs of sector i, $\boldsymbol{INT_i}$ (i.e., the internal component) is the CO_2 emissions generated when allocating the primary inputs of sector i to its own production, $\boldsymbol{FEB_i}$ (i.e., the feedback component) is the CO_2 emissions generated in sector i during the procedure of distributing the inputs used for subsequent returns from other sectors, and $\boldsymbol{SPI_i}$ (i.e., the spillover component) is the CO_2 emissions generated in other sectors to obtain the inputs when sector i initiated its productive activity.

4.3.5. Structural decomposition analysis extending the subsystem analysis

On the basis of the decomposition results derived from the subsystem analysis, SDA further explores the influencing factors behind the temporal changes in the components (including direct, internal, feedback and spillover components), which is expressed as follows.

$$\Delta \boldsymbol{e}_i(\Delta \boldsymbol{k}_i) = \Delta \boldsymbol{DIR}_i + \Delta \boldsymbol{INT}_i + \Delta \boldsymbol{FEB}_i + \Delta \boldsymbol{SPI}_i \qquad (4-40)$$

where $\Delta \boldsymbol{e}_i(\Delta \boldsymbol{k}_i)$ are changes in sector-level CO_2 emissions based on the demand-driven model (or the supply-driven model), each of the four terms (including $\Delta \boldsymbol{DIR}_i$, $\Delta \boldsymbol{INT}_i$, $\Delta \boldsymbol{FEB}_i$ and $\Delta \boldsymbol{SPI}_i$) represents the changes in a specific component of the CO_2 emissions for sector i.

Subsequently, the aforementioned equations are further decomposed as follows, according to the calculation of the new subsystem models proposed in Section 4.3.4.

$$\Delta \boldsymbol{DIR}_i = \Delta \boldsymbol{E}_i + \Delta \boldsymbol{Y}_i(\Delta \boldsymbol{V}_i) \qquad (4-41)$$

$$\Delta \boldsymbol{INT}_i = \Delta \boldsymbol{E}_i + \Delta \boldsymbol{I}_i + \Delta \boldsymbol{Y}_i(\Delta \boldsymbol{V}_i) \qquad (4-42)$$

$$\Delta \boldsymbol{FEB}_i = \Delta \boldsymbol{E}_i + \Delta \boldsymbol{F}_i + \Delta \boldsymbol{Y}_i(\Delta \boldsymbol{V}_i) \qquad (4-43)$$

$$\Delta \boldsymbol{SPI}_i = \Delta \boldsymbol{E}_j + \Delta \boldsymbol{S}_i + \Delta \boldsymbol{Y}_i(\Delta \boldsymbol{V}_i) \qquad (4-44)$$

where $\Delta \boldsymbol{E}_i$ is the contributions of carbon emission intensity (i.e., emissions per unit of output) to each of all components with the exception of the spillover component, $\Delta \boldsymbol{E}_j$ is the contributions of carbon emissions intensities of all sectors except sector i to the spillover component, $\Delta \boldsymbol{Y}_i(\Delta \boldsymbol{V}_i)$ is the contributions of final demand (or value-added) to each of all the components, $\Delta \boldsymbol{I}_i$ is the contributions of the technological level of sector i to the internal component, $\Delta \boldsymbol{F}_i$ is the contributions of sector-level technological levels to the feedback component, and $\Delta \boldsymbol{S}_i$ is the contributions of the inter-sector technological levels (or the inter-sector allocation relations) of all sectors except sector i to the spillover component in demand-driven (or supply-driven) model. To achieve this decomposition, the average of two polar decompositions is utilized in the study (Dietzenbacher and Los, 1998).

In view of the logic of the decomposition procedure, a CO_2 inventory could be constructed by quantifying the importance of carbon emissions intensity, technological levels and final demand (or value-added) to each component of total CO_2 emissions, which is detailed in Table 1. According to Table 1, there are 11 items to capture the influencing factors behind the temporal changes in CO_2 emissions for each sector. Besides, the CO_2 inventories are clarified into four categories according to the type of the input-output system (i.e., IOT or SAM) and the type of applied model (i.e., demand-driven model or supply-driven model). Further, to conduct the sector-level analysis of CO_2 inventories, the perspectives are from the maximum and minimum contributions of factors to CO_2 emissions changes, which demonstrate the lower and upper bounds of the sectoral impacts for each influencing factor. Thus, the sector-level analysis is conducted by comparing both the inter-sector and cross-sector results. In this way, the sector-specific experience in relation to CO_2 emission mitigation could facilitate the emissions reduction of the input-output system across all sectors (Chang, 2015; Wei et al., 2017).

Table 4-1 A CO_2 inventory framework within input-output systems

	Direct component		Initial component			Feedback component			Spillover component		
	ΔE_i	$\Delta Y(\Delta V)$	ΔE_i	ΔI	$\Delta Y(\Delta V)$	ΔE_i	ΔF	$\Delta Y(\Delta V)$	ΔE_j	ΔS	$\Delta Y(\Delta V)$
Sector 1											
Sector 2											
...											
Sector n											

4.3.6. Data

Three datasets are used in this study: time-series IOTs from 1997 to 2020, time-series SAMs from 1997 to 2020, and CO_2-related data. CO_2 emissions from 1997 to 2020 are calculated based on energy consumption, cement production and emission factor data. Energy consumption and cement production data are from China's National Bureau of Statistics, and emissions factor data are according to (Shan et al., 2018). Besides, the forecasts from 2021 to 2025, related to input-output systems and CO_2 emissions, are on the basis of the aforementioned three datasets from 1997 to 2020.

4.4. Results and discussion

4.4.1. Input-output forecasts validation

4.4.1.1. The performance evaluation of the EFM method

The simulative and predictive MSE of the EFM method obtains the best fitness, regardless of whether data are in-sample or out-of-sample. According to Table 4-2, for the in-sample group of typical sequences (i.e., $Y1$ to $Y5$), the MSE of MA method is 1.08e+02, 1.34e+04, 6.33e+01, 1.02e+02, and 1.61e+01. At the same time, the MFC method improves the performance of MA method: for the same sample group, the MSE of MFC method is 8.59e-29, 2.98e-27, 2.88e-29, 1.87e-27, and 6.86e-29. Then, the EFM method further enhances the performance of MFC method in this sample group. That is, the MSE of EFM method is 8.53e-29, 2.97e-27, 2.49e-29, 1.16e-27, and 5.88e-29. Similarly, when the out-of-sample group is considered, the EFM method outperforms the MA and MFC methods. For example, as shown in Table 2, the MSE of EFM method is 1.62e-28 for sequence $Y1$, which is higher than those of MA (3.75e+04) and MFC (4.34e-04) methods. This result is confirmed in the cases of $Y2$ to $Y5$.

Compared with the MA and MFC methods, the EFM method performs best in terms of the AME for both in-sample and out-of-sample data. According to Table 4-2, for in-sample data of typical sequences (i.e., $Y1$ to $Y5$), the AME of MA method is 6.92e+00, 6.73e+01, 5.60e+00, 6.55e+00, and 3.36e+00. For the same data, the AME of MFC method attains the lower value and it is 6.02e-15, 2.29e-14, 3.64e-15, 3.41e-14, and 6.48e-15; the AME of EFM method obtains the lowest value and it is 5.75e-15, 2.20e-14, 3.02e-15, 2.70e-14, and 5.42e-15. Furthermore, as for the out-of-sample data, the AME of EFM method is lower than those of MA and MFC methods, which shows the best performance of EFM method. For instance, the AME of sequence $Y1$ using EFM method is 5.68e-15, which is lower than those using MA (1.66e+02) and MFC (1.83e-02) methods. This finding is also consistent with the results of $Y2$ to $Y5$.

In comparison with MA and MFC methods, the EFM method attains the best performance in light of MAPE in both in-sample and out-of-sample data. According to Table 4-2, for the in-sample data of typical sequences, the MAPE of MA method is 3.72e-01, 4.26e-01, 2.89e-01, 9.71e-02, and 1.76e-01. The MFC method improves the performance of MA method, and its MAPE for in-sample data is 6.00e-16, 4.68e-16, 3.71e-16, 5.23e-16, and 4.56e-16. Further, the EFM method demonstrates the best performance and its MAPE is 3.90e-16, 3.16e-16, 1.89e-16, 4.33e-16, and 2.84e-16. These results are in the consistency with those for out-of-sample data: the EFM method possesses the best fitness. For example, the MAPE of EFM method for sequence $Y1$ is 3.65e-17 which is lower than those of MA (8.76e-01) and MFC (1.00e-04) methods.

To illustrate the best performance of the EFM method, CO_2 emissions are taken as an example. According to Table 4-3, for in-sample series, the MSE of CO_2 emissions by using EFM method is lower than those by using MA and MFC methods. For instance, as far as sector 1 is considered, its MSE of EFM method is 1.56e-26, which is lower than those of MA (1.33e+02) and MFC (1.61e-26) methods. The same conclusion is also shown in in-sample series in terms of AME and MAPE. Taking sector 1 as example, its AME of EFM method is 9.91e-14 lower than those of MA (8.46e+00) and MFC (1.01e-13) methods; its MAPE of EFM method is 1.33e-15 lower than those of MA (1.36e-01) and MFC (1.35e-15) methods. Then, for out-of-sample series, the EFM method possesses the lowest MSE when compared with MA and MFC methods. For instance, as for sector 1, the MSE of EFM method is 2.83e-28 lower than those of MA (8.21e+01) and MFC (9.28e-05) methods. Simultaneously, the EFM method has the lowest value of AME and MAPE when in contrast with MA and MFC methods. For example, for sector 1, the AME of EFM method is 1.42e-14 lower than those of MA (7.71e+00) and MFC (9.62e-03) methods; the MAPE of EFM method is 1.51e-16 lower than those of MA (7.80e-02) and MFC (1.00e-04) methods.

Table 4-2 Comparisons of simulation/prediction error of three models

Sequence	MA method			MFC method			EFM method		
	MSE	AME	MAPE	MSE	AME	MAPE	MSE	AME	MAPE
In-sample									
$Y1$ series	1.08e+02	6.92e+00	3.72e-01	8.59e-29	6.02e-15	6.00e-16	8.53e-29	5.75e-15	3.90e-16
$Y2$ series	1.34e+04	6.73e+01	4.26e-01	2.98e-27	2.29e-14	4.68e-16	2.97e-27	2.20e-14	3.16e-16
$Y3$ series	6.33e+01	5.60e+00	2.89e-01	2.88e-29	3.64e-15	3.71e-16	2.49e-29	3.02e-15	1.89e-16
$Y4$ series	1.02e+02	6.55e+00	9.71e-02	1.87e-27	3.41e-14	5.23e-16	1.16e-27	2.70e-14	4.33e-16
$Y5$ series	1.61e+01	3.36e+00	1.76e-01	6.86e-29	6.48e-15	4.56e-16	5.88e-29	5.42e-15	2.84e-16
Sequence	MA method			MFC method			EFM method		
	MSE	AME	MAPE	MSE	AME	MAPE	MSE	AME	MAPE
Out-of-sample									
$Y1$ series	3.75e+04	1.66e+02	8.76e-01	4.34e-04	1.83e-02	1.00e-04	1.62e-28	5.68e-15	3.65e-17
$Y2$ series	2.13e+07	3.62e+03	9.42e-01	2.22e-01	3.74e-01	1.00e-04	2.22e-01	3.74e-01	1.00e-04
$Y3$ series	1.26e+04	9.91e+01	8.15e-01	1.65e-04	1.17e-02	1.00e-04	1.62e-28	5.68e-15	2.79e-17
$Y4$ series	6.38e+01	6.48e+00	9.75e-02	5.04e-05	7.05e-03	1.00e-04	1.50e-05	2.88e-03	3.94e-05
$Y5$ series	1.99e+02	1.37e+01	3.91e-01	1.22e-05	3.47e-03	1.00e-04	1.04e-05	2.87e-03	8.00e-05

Table 4-3 Comparisons of simulation/prediction error of three models in the case of CO_2 emissions

Sector	MA method			MFC method			EFM method		
	MSE	AME	MAPE	MSE	AME	MAPE	MSE	AME	MAPE
In-sample									
$S1$	1.33e+02	8.46e+00	1.36e-01	1.61e-26	1.01e-13	1.35e-15	1.56e-26	9.91e-14	1.33e-15
$S2$	3.44e+02	1.28e+01	1.45e-01	2.84e-26	1.13e-13	1.47e-15	2.84e-26	1.13e-13	1.47e-15
$S3$	1.49e+01	3.04e+00	7.20e-02	4.38e-27	5.27e-14	1.25e-15	4.38e-27	5.27e-14	1.25e-15
$S4$	1.37e+01	2.25e+00	1.36e-01	1.12e-27	2.36e-14	1.55e-15	1.12e-27	2.36e-14	1.55e-15
$S5$	4.75e+00	1.74e+00	1.27e-01	5.66e-28	1.76e-14	1.33e-15	5.66e-28	1.76e-14	1.33e-15
$S6$	1.31e+02	8.03e+00	9.59e-02	2.04e-26	1.10e-13	1.41e-15	2.00e-26	1.05e-13	1.33e-15
$S7$	3.47e+01	4.21e+00	1.13e-01	3.67e-27	4.96e-14	1.44e-15	3.50e-27	4.66e-14	1.35e-15
$S8$	2.67e+00	1.18e+00	1.22e-01	2.45e-28	1.28e-14	1.53e-15	2.45e-28	1.28e-14	1.53e-15
$S9$	2.61e+00	1.20e+00	1.13e-01	3.50e-28	1.47e-14	1.47e-15	3.50e-28	1.47e-14	1.47e-15
$S10$	4.11e+01	5.16e+00	1.27e-01	4.89e-27	5.63e-14	1.50e-15	4.89e-27	5.63e-14	1.50e-15
$S11$	1.81e+02	1.12e+01	1.11e-01	3.58e-26	1.38e-13	1.33e-15	3.54e-26	1.34e-13	1.23e-15
$S12$	1.30e+03	2.65e+01	1.40e-01	1.88e-25	3.19e-13	1.45e-15	1.82e-25	3.03e-13	1.35e-15
$S13$	1.55e+04	1.02e+02	1.20e-01	3.06e-24	1.24e-12	1.40e-15	3.03e-24	1.20e-12	1.30e-15
$S14$	3.63e+04	1.57e+02	1.46e-01	5.75e-24	1.62e-12	1.39e-15	5.72e-24	1.58e-12	1.29e-15
$S15$	4.60e+00	1.60e+00	1.05e-01	5.45e-28	1.94e-14	1.40e-15	5.45e-28	1.94e-14	1.40e-15
$S16$	5.95e+01	6.02e+00	1.91e-01	3.91e-27	4.65e-14	1.62e-15	3.91e-27	4.65e-14	1.62e-15
$S17$	2.98e+00	1.33e+00	1.04e-01	4.14e-28	1.68e-14	1.40e-15	3.94e-28	1.58e-14	1.32e-15
$S18$	5.70e+00	1.67e+00	8.60e-02	1.14e-27	2.66e-14	1.43e-15	1.14e-27	2.66e-14	1.43e-15
$S19$	3.18e+00	1.31e+00	1.40e-01	2.49e-28	1.32e-14	1.59e-15	2.40e-28	1.25e-14	1.49e-15
$S20$	1.35e+00	8.34e-01	1.49e-01	6.94e-29	7.11e-15	1.47e-15	6.94e-29	7.11e-15	1.47e-15
$S21$	3.80e-02	1.41e-01	1.12e-01	3.55e-30	1.64e-15	1.41e-15	3.55e-30	1.64e-15	1.41e-15
$S22$	2.05e+00	8.90e-01	2.07e-01	9.82e-29	7.81e-15	1.26e-15	8.16e-29	6.87e-15	1.19e-15
$S23$	1.38e+05	3.05e+02	1.22e-01	2.49e-23	3.43e-12	1.31e-15	2.47e-23	3.31e-12	1.20e-15
$S24$	1.06e+00	7.07e-01	2.63e-01	3.02e-29	4.38e-15	1.35e-15	3.02e-29	4.38e-15	1.35e-15

$S25$	7.90e-03	6.92e-02	1.17e-01	9.82e-31	8.44e-16	1.39e-15	9.29e-31	7.92e-16	1.29e-15
$S26$	1.29e+01	2.90e+00	8.90e-02	2.98e-27	4.01e-14	1.27e-15	2.94e-27	3.87e-14	1.18e-15
$S27$	3.53e+03	5.25e+01	1.35e-01	6.34e-25	5.50e-13	1.33e-15	6.32e-25	5.40e-13	1.25e-15
$S28$	5.17e+01	5.92e+00	1.01e-01	1.18e-26	7.74e-14	1.31e-15	1.17e-26	7.52e-14	1.23e-15
$S29$	1.81e+02	1.15e+01	9.74e-02	4.04e-26	1.46e-13	1.22e-15	4.04e-26	1.46e-13	1.22e-15
$S30$	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00
$S31$	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00
$S32$	1.17e+02	8.60e+00	6.73e-02	3.70e-26	1.50e-13	1.21e-15	3.54e-26	1.41e-13	1.13e-15
$S33$	2.91e+02	1.38e+01	8.79e-02	6.52e-26	1.95e-13	1.30e-15	6.37e-26	1.86e-13	1.22e-15
$S34$	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00

Sector	MA method			MFC method			EFM method		
	MSE	AME	MAPE	MSE	AME	MAPE	MSE	AME	MAPE
Out-of-sample									
$S1$	8.21e+01	7.71e+00	7.80e-02	9.28e-05	9.62e-03	1.00e-04	2.83e-28	1.42e-14	1.51e-16
$S2$	4.53e+03	6.65e+01	1.28e+00	3.27e-05	5.62e-03	1.00e-04	2.33e-05	4.25e-03	8.00e-05
$S3$	2.78e+01	5.15e+00	1.32e-01	1.55e-05	3.93e-03	1.00e-04	0.00e+00	0.00e+00	0.00e+00
$S4$	1.06e+02	1.02e+01	8.07e-01	1.68e-06	1.29e-03	1.00e-04	1.21e-06	9.83e-04	8.00e-05
$S5$	2.45e+01	4.69e+00	3.71e-01	1.81e-06	1.34e-03	1.00e-04	1.51e-06	1.09e-03	8.00e-05
$S6$	1.66e+03	3.83e+01	7.37e-01	3.83e-05	6.02e-03	1.00e-04	2.51e-05	4.39e-03	8.00e-05
$S7$	5.95e+02	2.38e+01	2.09e+00	2.42e-06	1.45e-03	1.00e-04	0.00e+00	0.00e+00	0.00e+00
$S8$	4.70e+01	6.59e+00	3.33e+00	1.45e-07	3.25e-04	1.00e-04	9.86e-33	4.44e-17	3.61e-17
$S9$	8.59e+01	9.06e+00	3.57e+00	1.70e-07	3.61e-04	1.00e-04	1.15e-07	2.24e-04	6.00e-05
$S10$	6.85e+02	2.54e+01	1.43e+00	5.04e-06	2.14e-03	1.00e-04	6.31e-31	3.55e-16	2.32e-17
$S11$	4.13e+02	1.58e+01	9.69e-02	2.35e-04	1.52e-02	1.00e-04	2.34e-05	3.65e-03	2.50e-05
$S12$	1.08e+04	8.77e+01	5.40e-01	4.65e-04	2.08e-02	1.00e-04	1.77e-04	1.01e-02	6.00e-05
$S13$	1.87e+04	1.26e+02	1.12e-01	1.33e-02	1.15e-01	1.00e-04	1.03e-26	4.55e-14	3.94e-17
$S14$	1.57e+04	9.69e+01	5.05e-02	3.41e-02	1.84e-01	1.00e-04	9.54e-03	6.94e-02	3.67e-05

$S15$	7.66e+01	8.19e+00	4.29e-01	4.87e-06	2.06e-03	1.00e-04	2.73e-07	4.33e-04	2.50e-05
$S16$	4.23e+02	1.99e+01	1.34e+00	3.44e-06	1.76e-03	1.00e-04	0.00e+00	0.00e+00	0.00e+00
$S17$	6.85e+01	7.89e+00	2.27e+00	3.31e-07	5.12e-04	1.00e-04	2.22e-07	3.64e-04	8.00e-05
$S18$	2.11e+02	1.41e+01	1.90e+00	9.92e-07	9.36e-04	1.00e-04	1.42e-30	8.88e-16	1.38e-16
$S19$	4.67e+01	6.71e+00	2.94e+00	1.11e-07	3.01e-04	1.00e-04	2.28e-08	1.16e-04	6.00e-05
$S20$	1.17e+00	1.05e+00	2.95e-01	1.35e-07	3.66e-04	1.00e-04	0.00e+00	0.00e+00	0.00e+00
$S21$	5.57e-01	7.23e-01	2.05e+00	2.47e-09	4.57e-05	1.00e-04	1.26e-09	3.02e-05	8.00e-05
$S22$	5.14e+00	1.89e+00	3.70e-01	3.00e-07	5.03e-04	1.00e-04	1.17e-07	2.61e-04	4.90e-05
$S23$	4.00e+05	5.65e+02	1.24e-01	1.95e-01	4.40e-01	1.00e-04	1.95e-01	4.40e-01	1.00e-04
$S24$	4.12e+00	1.80e+00	6.59e-01	1.15e-07	3.00e-04	1.00e-04	5.74e-09	5.99e-05	2.50e-05
$S25$	5.46e-02	2.15e-01	6.47e-01	1.62e-09	3.92e-05	1.00e-04	1.24e-09	3.05e-05	8.00e-05
$S26$	2.07e+01	4.31e+00	9.45e-02	2.05e-05	4.52e-03	1.00e-04	9.01e-06	2.37e-03	5.23e-05
$S27$	1.80e+04	1.32e+02	1.85e-01	5.10e-03	7.14e-02	1.00e-04	2.38e-03	3.87e-02	5.32e-05
$S28$	1.44e+02	1.05e+01	1.55e-01	5.55e-05	7.39e-03	1.00e-04	1.53e-05	2.47e-03	3.17e-05
$S29$	1.18e+02	8.30e+00	4.93e-02	2.64e-04	1.62e-02	1.00e-04	1.19e-04	8.59e-03	5.32e-05
$S30$	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00
$S31$	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00
$S32$	4.78e+02	1.74e+01	9.88e-02	2.81e-04	1.67e-02	1.00e-04	1.57e-04	1.07e-02	6.67e-05
$S33$	5.57e+03	7.39e+01	2.77e-01	7.08e-04	2.66e-02	1.00e-04	7.08e-04	2.66e-02	1.00e-04
$S34$	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00

4.4.1.2. The uncertainty of input-output forecasts

The uncertainty level of the forecasted IOTs remains stable and level from 2021 to 2025. In detail, at the aggregate level, the Z-scores of the upper bounds of the uncertainty are around 1.945 and the Z-scores of the lower bounds of the uncertainty are about -1.952 from 2021 to 2025. At the sector level, the distribution of Z-scores is stable, and the Z-scores exhibit positively skewed distributions as the median values are less than the mean values. In the meantime, some sectors and sector transactions exert larger impacts on the distribution (Figure 4-1a). For example, the sector contributing most to the uncertainty is sector 12 (*Manufacture of Chemicals and Chemical Products*). Also, the sector transaction generating most influence is from sector 12 (*Manufacture of Chemicals and Chemical Products*) to sector 12 (*Manufacture of Chemicals and Chemical Products*). Similarly, the uncertainty level of the forecasted SAMs stays level between 2021 and 2025. To illustrate, at the aggregate level, the Z-scores of the upper bounds of the uncertainty achieve about 1.945 and the Z-scores of the lower bounds reach about -1.950 from 2021 to 2025. At the sector level, the distribution of Z-scores is steady, and the Z-scores present positively skewed distributions (Figure 4-1b). Meanwhile, some economic activities and economic transactions have larger impacts on the distribution. For instance, the economic activity contributing most to the uncertainty is economic activity 46 (*Urban Household Account*). Also, the economic transaction with most influence is from economic activity 51 (*Others Account*) to 43 (*Labour Factor Account*).

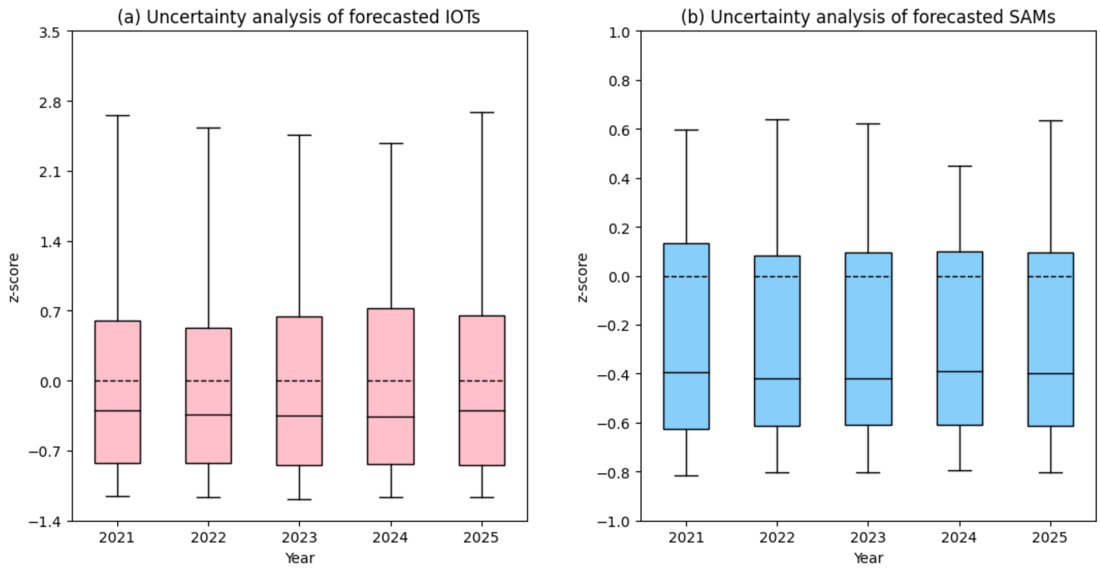

Figure 4-1 Uncertainty analyses of the forecasted input-output systems

4.4.2. The overview of CO_2 inventories from 1997 to 2025

The CO_2 inventories are clarified into four categories, which depict the contributions of 11 influencing factors behind temporal changes in sector-level CO_2 emissions transmitting throughout the IOT- and SAM-related production systems in the contexts of demand- and supply-driven models. In the meantime, the CO_2 inventories span a period of time from 1997 to 2025, describing the past from 1997 to 2020 and the forecasts from 2021 to 2025. According to Table 1, each CO_2 inventory is in a uniform format and is a $n * 11$ matrix. In the row direction, there are 11 items to inform the contributions of 11 influencing factors to the emissions changes of each sector. In the column direction, the emissions changes arising from each of the aforementioned 11 items are distributed among n sectors.

4.4.3. Contributions of components to CO_2 emissions

In the context of the demand-driven IOT model, the spillover component contributed most to CO_2 emissions from 1997 to 2020 and is expected to continue the tendency between 2021 and 2025 (Figure 4-2a). In the meantime, CO_2 emissions from all components except the spillover component tend to reach a plateau from 2020 onwards

(Figure 4-2a). For example, the share of the spillover component's contribution in total CO_2 emissions increased from 83% in 1997 to 86% in 2020, and in 2025 the spillover component is forecasted to generate 86% of total CO_2 emissions. These results indicate that most CO_2 emissions were generated and are projected to be generated because of the interconnections among sectors (i.e., the true polluting backward linkages that a specific sector produces in the other sectors of the economy) (Sanchez-Choliz, 2003). In this regard, it is necessary to continue and update the supply chain management in moderating the level of CO_2 emissions (Gui et al., 2014; Yuan et al., 2018; J. Li et al., 2018; C.-W. Sun et al., 2020). For instance, it is achievable to select suppliers with the provision of products with low-carbon labels to promote low-carbon technologies (J. Li et al., 2018; Wen and Wang, 2019).

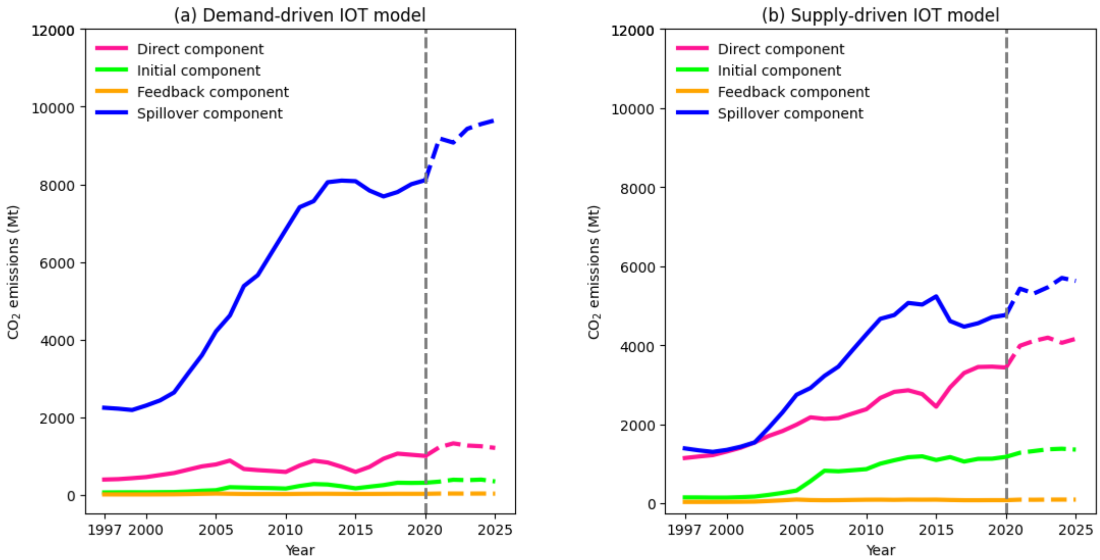

Figure 4-2 Contributions of components to CO_2 emissions within IOT-related system

On the contrary, in the supply-driven IOT model, although the spillover component contributed and is excepted to contribute most to total CO_2 emissions, the gap between the spillover component and the direct component remained is excepted to remain smaller than that in the demand-driven IOT model (Figure 4-2b). For example, the gap was 9% in 1997, increased to 14% in 2020 and is projected to reach 13% in 2025. These results indicate besides the importance of spillover component, the IOT-related production system generated and is projected to generate a large amount of CO_2 emissions without depending on the linked production activities. Therefore, not only are the interconnections among sectors crucial, but the role of direct supply is also vital for CO_2 emissions reduction. For example, fostering the low-carbon concept at the start of supply chains, and using low-carbon raw materials could promote low-carbon outputs (Xie et al., 2017; Wen and Wang, 2019). In the meantime, improving the efficiency of primary inputs by training, and relocating the primary inputs from high to low carbon-intensive sectors, could be feasible during the eco-friendly production process (Jawad Sajid et al., 2021; Song et al., 2020).

Based on the SAM-related models, the spillover component remained and is projected to remain the largest component of total CO_2 emissions (Figure 4-3a), which is consistent with the findings using the IOT-related models. In detail, in the demand-driven SAM case, the share of spillover component was 94% in both 1997 and 2020. In 2025, this component is projected to reach 93% of total CO_2 emissions. In the supply-driven SAM case, the spillover component generated 84% of total CO_2 emissions in 1997 and 86% of total emissions in 2020. And then it is expected to contribute generating 84% of total CO_2 emissions in 2025.

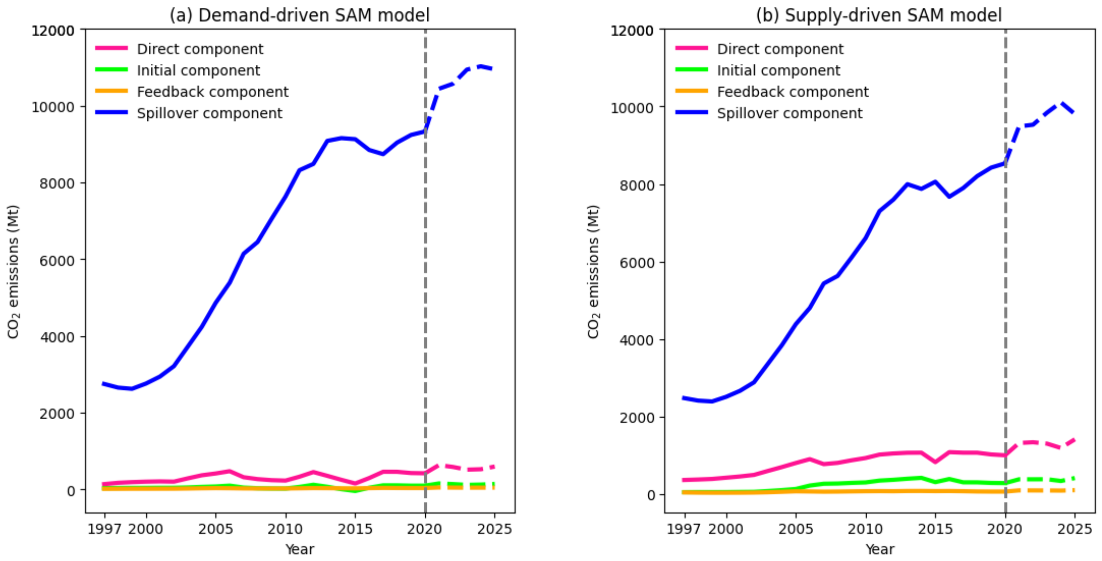

Figure 4-3 Contributions of components to CO_2 emissions within SAM-related system

But at the same time, in the context of supply-driven SAM model, the contributions from all components except the spillover component were small and are projected to continue this trend (Figure 4-3b), which is different from the results using the supply-driven IOT model. For instance, the shares of all components with the exception of the spillover component were 12%, 2% and 2% respectively in 1997. Then, the rates were severally 10%, 3% and 1% in 2020. And in 2025, they are forecasted to reach 12%, 3% and 1%, respectively. Also, the share of the spillover component derived from the SAM-related models is larger than that according to the calculation of IOT-related models. In summary, these results indicate that within the SAM framework, most CO_2 emissions are transmitted by means of the interdependence among production and distribution activities (Cardenete et al., 2012; Y.-Z. Li et al., 2018), which deserves more attention regarding CO_2 emissions reduction (Wood, 2009).

4.4.4. Contributions of factors to CO_2 emissions changes

In the context of the demand-driven IOT model, the final demand was the largest determinant of CO_2 emissions increases for most of the years from 1997 to 2020, and it is expected to continue its effects from 2021 onwards (Figure 4-4a). In the meantime, the impacts from inter-sector technological levels and emissions intensities of upstream sectors fluctuated between 1997 and 2020. The former is forecasted to make small contributions to CO_2 emissions decreases from 2021 to 2025 during which the latter is predicted to make larger contributions to CO_2 emissions decline (Figure 4-4a). These results imply that it is of necessity to advocate sustainable consumption and to optimize final demand structure (Butnar and Llop, 2011; Yang et al., 2015b; Yuan and Zhao, 2016; Q.-P. Li et al., 2021). Also, exploiting the potentials of inter-sector technological levels and emissions intensities of upstream sectors in CO_2 emissions reduction is of importance (Lim et al., 2009). For example, to improve the inter-sectoral technological innovation, measures, such as carbon footprint label certification, carbon tax and reports concerning emissions from upstream activities, could be effective (J. Li et al., 2018). For another example, the potentials of emissions intensities of upstream sectors could be derived from the optimization of fuel mix and the enhancement of energy efficiency (Gui et al., 2014; J. Li et al., 2018).

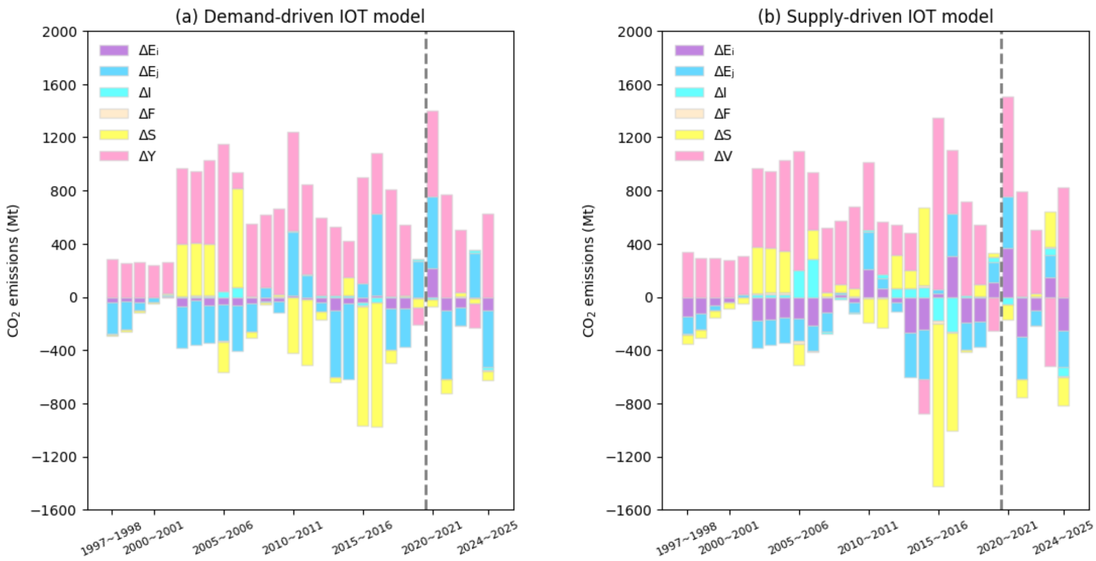

Figure 4-4 Contributions of factors to CO_2 emissions changes within IOT-related system

When it comes to the supply-driven IOT model, the value-added contributed most to

CO_2 emissions increases between 1997 and 2020 and is forecasted to continue the trend from 2021 to 2025 (Figure 4-4b). Meanwhile, the impacts of inter-sector allocation relations on CO_2 emissions increases fluctuated during 1997-2020 and are predicted to make small contributions to CO_2 emissions decreases starting from 2021. In addition, the effects of emissions intensities experienced fluctuations between 1997 and 2020, and are expected to continue decreasing CO_2 emissions from 2021 to 2025 compared with the level of the impacts of emissions intensities during 1997-2020. These results imply that to mitigate CO_2 emissions, more attentions could be drawn to reducing the impacts from primary inputs and inter-sector allocation relations (Wood, 2009), and to exploiting the potentials of emissions intensities in decreasing CO_2 emissions (Lim et al., 2009). For instance, CO_2 emissions reduction measures for sectors whose primary inputs induce large downstream CO_2 emissions could include decreasing subsidies, increasing revenue tax, regulating product prices, and restricting loan supply. Also, providing additional supports, such as financial intensives, for selling products on low-carbon users is needed. In addition, optimizing fuel mix, and enhancing energy efficiency, could be feasible in terms of CO_2 emissions alleviation (Zhang, 2010; Gui et al., 2014; Liang et al., 2017; J. Li et al., 2018).

Using the demand-driven SAM model, the results show that final demand has been the most important influencing factor contributing to CO_2 emissions increases for most years since 1997, and is forecasted to continue this trend from 2021 to 2025 (Figure 4-5a). But at the same time, the impacts of emissions intensities of upstream sectors experienced fluctuations between 1997 and 2020, and they are projected to be the most vital influencing factor in CO_2 emissions decreases starting from 2021. Also, the impacts of inter-sector technological levels fluctuated over the period from 1997 to 2020, and they are forecasted to exert the impacts of fluctuations on CO_2 emissions from 2021 onwards. These results indicating the important roles of the three influencing factors are consistent with the findings in the demand-driven IOT model. These results indicate that when the distribution of institutions and factor accounts is considered (Cardenete et al., 2012; Y.-Z. Li et al., 2018), not only is the final demand important, but the emissions intensities of upstream sectors are also crucial to alleviate CO_2 emissions (Wood, 2009). Besides, coping with the impacts from inter-sector technological levels is the common issue within IOT- and SAM-related production systems from the demand side (Lim et al., 2009).

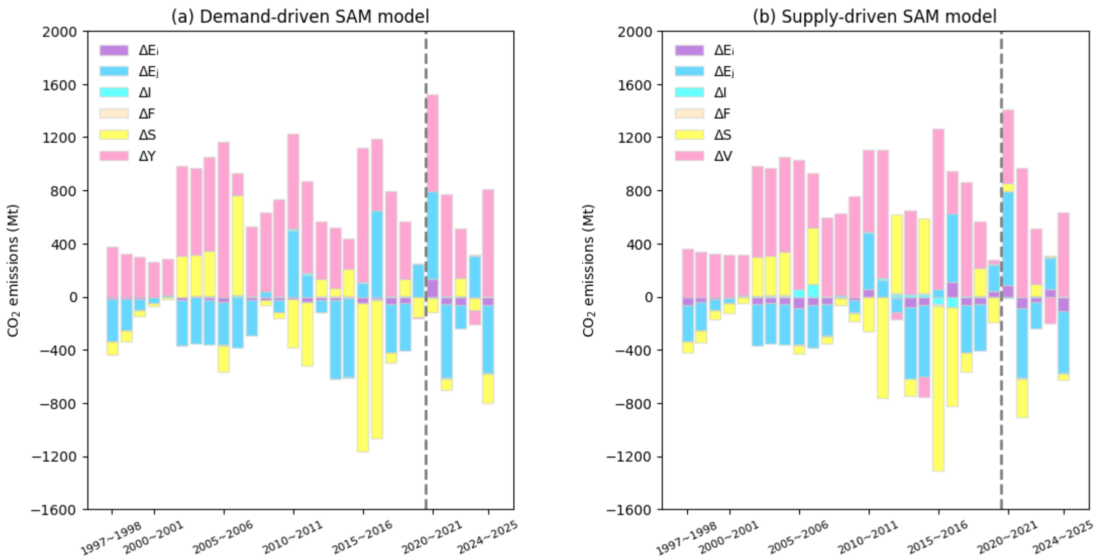

Figure 4-5 Contributions of factors to CO_2 emissions changes within SAM-related system

When using the supply-driven SAM model, the results show that the contributions of value-added to CO_2 emissions increases remained the largest for most of the years from 1997 to 2020, and they are forecasted to be in the first position between 2021 and 2025 (Figure 4-5b). On the contrary, the effects of emissions intensities of downstream sectors fluctuated from 1997 to 2020, and they are forecasted to amount to the highest level of CO_2 emissions decreases from 2021 to 2025. Also, the influences of inter-sector allocation relations experienced fluctuations from 1997 to 2020, and they are forecasted to make smaller contributions to CO_2 emissions decreases between 2021 and 2025.

According to the results above, to decrease CO_2 emissions within the SAM framework (Cardenete et al., 2012; Y.-Z. Li et al., 2018), reducing the impacts from the value-added deserves more efforts in CO_2 emissions reduction (Wood, 2009); meanwhile managing the effects of inter-sector allocation relations and emissions intensities of downstream sectors could be supportive in offsetting emissions increases (Lim et al., 2009).

4.4.5. Sector-level analysis of CO_2 inventories from 2020 to 2021

The newly constructed CO_2 inventories could not only inform dynamically the emissions channels arising from the interdependence among sectors within an economic system, but could also extend this holistic perspective of analysing CO_2 emissions from demand and supply sides (Yuan et al., 2017; Fan et al., 2018). Furthermore, the sector-level analysis is conducted by comparing both the inter-sector and cross-sector results. In this way, the sector-specific experience pertaining to CO_2 emission alleviation could facilitate the emissions reduction of the input-output system across all sectors (Chang, 2015; Wei et al., 2017).

In the demand-driven IOT model context, the main contributing factors in sector-level CO_2 emissions increases are projected to include the final demand and emissions intensities upstream (Figure 4-6a). Especially, the maximum contributions of factors to CO_2 emissions increase are projected to be mainly from the final demands of sectors 26 (*Construction*) and 14 (*Manufacture and Processing of Metals*), and the emissions intensities upstream of sector 26. On the contrary, the minimum contributions of factors to emissions increases are projected to come from the final demands of sectors 23 (*Production and Supply of Electricity and Steam*) and 29 (*Other Services*), and the inter-sector technological levels of sector 18 (*Manufacture of Transport Equipment*). These results provide the following implications. Because of the promotion of urbanization and industrialization in China, there are a large amount of requirements for various kinds of machinery/equipment (Q.-M. Liang et al., 2016), which induces the impacts of final demand on CO_2 emissions increases. In the meantime, resolving the contradiction of excess capacity is one of main tasks of the supply-side reform in China (Ouyang et al., 2020). Against the background, it is of necessity for sectors to strengthen the technological innovation, phase out backward technologies and equipment, eliminate backward capacity, promote sustainable consumption, and optimize final demand structure (Butnar and Llop, 2011; Yang et al., 2015b; Yuan and Zhao, 2016; Q.-P. Li et al., 2021; Ouyang et al., 2020). For example, as far as sector 26 is considered, measures to achieve carbon abatement could include controlling the expansion of infrastructure and construction activity workloads, and promoting material-use efficiency (Bai et al., 2018). But at the same time, it is of importance to learn from sectors 23 and 29 when considering the experience of how to reduce the impacts of final demand on CO_2 emissions increases. Apart from the considerations surrounding the role of final demand, exploiting the potentials of other influencing factors for CO_2 emissions reduction is also of significance. For example, for sector 23, measures to reduce CO_2 emissions could also be related to enhancing the technologies of energy generation, introducing wind, biomass and land fill energy generation, and promoting more efficient ways to use electricity (L.-C. Liu et al., 2016).

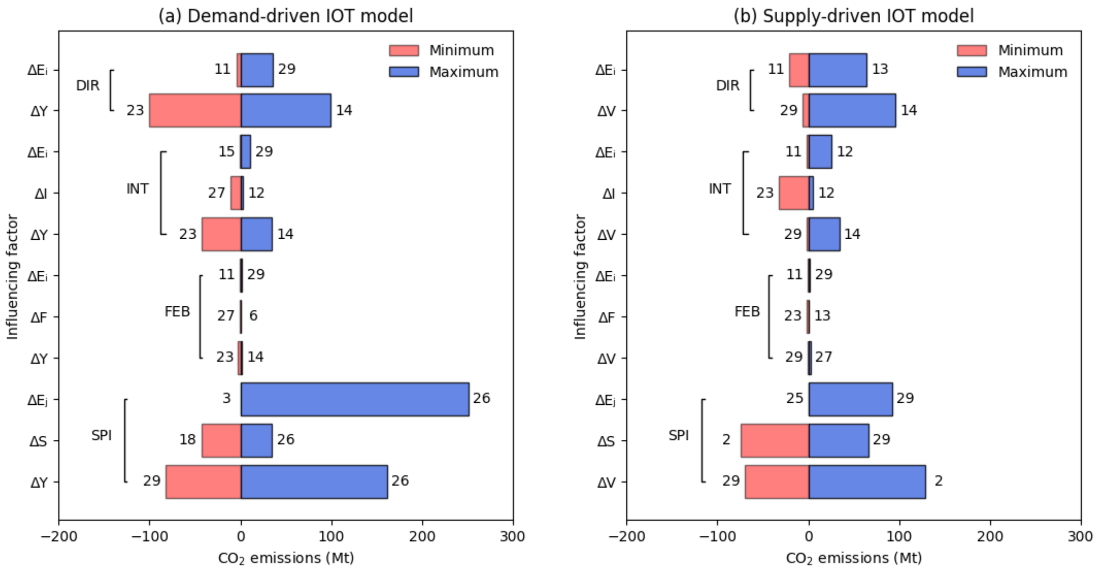

Figure 4-6 Contributions of factors to sector-level CO_2 emissions increases using IOTs

The results of supply-driven IOT model shows the main factors increasing sector-level CO_2 emissions are excepted to include the value-added and inter-sector allocation relations (Figure 4-6b). Specifically, the maximum contributions of factors to CO_2 emissions increases are projected to be primarily from the value-added of sectors 2 (*Mining and Washing of Coal*) and 14 (*Manufacture and Processing of Metals*), and the emissions intensities downstream of sector 29 (*Other Services*). By contrast, the minimum contributions of factors to emissions increases are projected to be mainly from the inter-sector allocation relations of sector 2 (*Mining and Washing of Coal*), and the value-added of sector 29 (*Other Services*). Except for the measures to cope with the pushing effects from value-added in Section 4.4.4, measures concerning the emissions intensities downstream could include encouraging the downstream sectors to develop towards low-carbonization by regulations, transferring technologies and capital investments (Zhang, 2010; Liang et al., 2017; J. Li et al., 2018). Also, regarding the CO_2 emissions reduction in service sectors, current studies detail the importance of shifting from secondary sectors to service sectors (C. Zhang et al., 2019), and the upgrading of traditional services sectors (Zhang et al., 2016). Thus, the experience of sector 29 in reducing the impacts of value-added on CO_2 emissions increases could be learned by other sectors, according to the results above. In addition, learning from the experience of sector 2 decarbonizing the allocation behaviours (i.e., the allocation relations between sector 2 and sector 2's downstream sectors) is also advocated in terms of CO_2 emissions reduction (Liang et al., 2017; J. Li et al., 2018).

Using the demand-driven SAM model, the main factors in increasing CO_2 emissions are predicted to be the final demand and emissions intensities upstream (Figure 4-7a). For example, the maximum contributions of factors are predicted to be mainly from the final demands of sectors 26 (*Construction*) and 14 (*Manufacture and Processing of Metals*), and the emissions intensities upstream of sector 26. On the contrary, the minimum contributions of factors are predicted to be primarily from the final demand of sector 29 (*Other Services*), and the inter-sector technological levels of sector 18 (*Manufacture of Transport Equipment*). At the same time, these results tend to concentrate most on the spillover component of CO_2 emissions changes. These results indicate that the spillover component is where to put more efforts in CO_2 emissions reduction (Wood, 2009), which is consistent with the implications from the aggregate results in Section 4.4.3. These results above show some differences with the findings based on the demand-driven IOT model. This is because in the SAM framework, the distribution among economic activities extends the inter-sector relations derived from the IOT framework (Cardenete et al., 2012; Y.-Z. Li et al., 2018), with which the CO_2 emissions channels change.

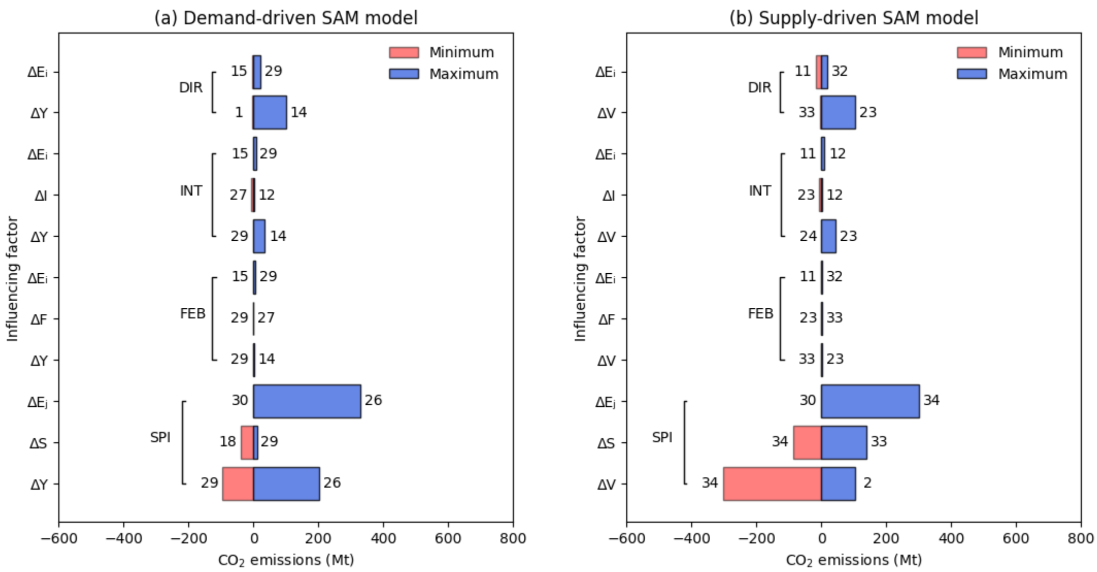

Figure 4-7 Contributions of factors to sector-level CO_2 emissions increases using SAMs

In the supply-driven SAM model context, the main factors in sector-level CO_2 emissions increases are forecasted to be the value-added, emissions intensities downstream, and inter-sector allocation relations (Figure 4-7b). To illustrate, the maximum contributions of factors are projected to be mainly from the value-added of sectors 23 (*Production and Supply of Electricity and Steam*) and 2 (*Mining and Washing* *of Coal*), the emissions intensities downstream of sector 34 (*Enterprise account*), and the inter-sector allocation relations of sector 33 (*Urban Household account*). Conversely, the minimum contributions of factors are forecasted to be primarily from the value-added and inter-sector allocation relations of sector 34. The differences between supply-driven SAM and IOT models are more than those between demand-driven SAM and IOT models. This indicates that when the distribution among institutions and factor accounts is considered in the SAM framework (Cardenete et al., 2012; Y.-Z. Li et al., 2018), the importance of economic agents (e.g., enterprises and households) to CO_2 emissions reduction and the impacts of production sectors such as sectors 23 and 2 on CO_2 emissions alleviation are emphasized in the context of supply-driven case. Besides the measures to cope with the pushing effects from value-added in Section 4.4.4, the efforts of sector 33 in terms of the allocation of the primary inputs to low-carbon sectors could be further enhanced (Chen et al., 2019). Furthermore, there are some studies analysing the current status and drivers of CO_2 emissions at the enterprise level. To address the emissions increases of sector 34, measures, such as promoting the market-oriented reforms, enhancing regulatory enforcement, introducing higher standards, utilizing the taxation tool, investing on low-carbon technologies through green finance, improving the sharing of sector-level experience, upgrading high-polluting industries, and optimizing the distribution proportion of intermediate products, could be feasible (Meng et al., 2018; Xie et al., 2018; Y. Li et al., 2020). But at the same time, learning from the efforts of sector 34 in reducing the impacts of value-added and inter-sector allocation relations on CO_2 emissions, e.g., the optimization of investment directions (F. Wang et al., 2021) and the selection of downstream sectors to promote technological innovation and low-carbon transformation (Hou et al., 2021), is of importance for CO_2 emissions reduction.

4.5. Conclusion

To forecast the input-output systems including IOTs and SAMs, we propose a procedure of input-output forecasting. During this procedure, the input-output table series are forecasted by proposing an element-based Fourier-Markov (EFM) method, then structured through the MMTT method and T-accounts concept, and last, validated by combining matrix calculation methods with Monte Carlo simulations. On the basis of the forecasted table series, we construct CO_2 inventories by proposing a new integrated method, that is, the combination of subsystem analysis with SDA. This study is in the case of China from 1997 to 2025.

In this study, the performance evaluation of the EFM method is conducted and shown in the cases of typical sequences and CO_2 emissions. Simulative and predictive results support that the EFM method attains the best fitness. Then, the forecasted IOTs and SAMs span a period of time from 2021 to 2025, during which the uncertainty levels of these forecasted table series remain stable and level. Based on the forecasted IOTs and SAMs, the CO_2 inventories are constructed and then clarified into four categories, which depict the contributions of 11 influencing factors behind temporal changes in sector-level CO_2 emissions transmitting throughout the IOT- and SAM-related production systems in the contexts of demand- and supply-driven models.

The main results are summarized as follows. First, the spillover component was the largest determinant of CO_2 emissions and is forecasted to continue this tendency. Second, the final demand (or value-added) remained and are projected to be the factor contributing most to emissions increases in the demand-driven model (or supply-driven model). Third, the effects of other influencing factors to emissions changes differed and are forecasted to differ, depending on the type of input-output system, and whether the model is demand-driven or supply-driven. Last, the sector-level performance is forecasted to be different for each category of CO_2 inventories, but the sector-level analysis by way of the maximum and minimum measurements of CO_2 emissions changes could provide supports for the carbon abatement across all sectors. Accordingly, the main carbon implications are proposed as follows. First, it is of necessity to continue and update the supply chain management in moderating the level of CO_2 emissions. Second, measures, related to the optimization of final demand and the reasonable use of primary inputs, could be effective in alleviating CO_2 emissions. Third, exploiting the potentials of other selected influencing factors (e.g., emissions intensities, inter-sector technological levels, and inter-sector allocation relations) could be feasible for reducing CO_2 emissions. Last, corresponding to the idea of sector-level analysis introduced in section 4.3.5, as for each of the 11 influencing factors, the sector-specific experience of decreasing CO_2 emissions could be generalized and shared among sectors.

Chapter 5: An integrated scheme of input-output future scenarios construction interconnecting production with consumption and sector-level CO_2 emissions synergic alleviation

5.1. Introduction

Input-output analysis (IOA) in the scenario context has been increasingly investigated in response to the explorations in terms of strategic planning and anticipation on future development (Faber et al., 2007). This integrated analysis could encompass the inter- and intra-linkages between sectors in the design of future scenarios (Carvalho et al., 2015; Oliveira et al., 2016), identify the potential pathways for the future development of external variables and suggest the corresponding measures to take in the future (Mi et al., 2015; Yu et al., 2016b). Besides, with this integrative analysis, input-output future scenarios could be formulated and analytical under specific conditions (Rao et al., 2018; Rojas Sánchez et al., 2019).

During the procedure of integrating IOA and scenario analysis, multi-criteria decision making (MCDM) has been found to be feasible and useful. This is because not only does MCDM suit the real world problems involving multiple, conflicting and incommensurable objectives (Oliveira and Antunes, 2004; San Cristóbal, 2012; Oliveira et al., 2016), but this technique also provides an approach towards the trade-offs among multiple attributes and multiple objectives (Weng et al., 2010; De Carvalho et al., 2016; Abdullah et al., 2021). For example, multi-attribute decision making methods (i.e., the first category of MCDM) are used to allocate CO_2 emissions among sectors by considering the impacts of various attributes in terms of capacity, responsibility, and potential (Zhao et al., 2017). For another example, multi-objective optimization methods (i.e., the second category of MCDM) are used to investigate whether energy savings goal is achieved when the decision-making process is confronted with multiple objectives in terms of economy, energy and environment (S.-

W. Yu et al., 2018b).

However, it is also noted that the interconnections between production and consumption have not been emphasized during the process where IOA is integrated with scenario analysis by means of MCDM, in spite of these interconnections fundamentally characterizing the IOA scheme and related extensions to the field of environment (Oliveira and Antunes, 2004; Weng et al., 2010; Carvalho et al., 2015; Oliveira et al., 2016; Rojas Sánchez et al., 2019). Further, corresponding to the interconnections between production and consumption within input-output future scenarios, some concerns need to be dealt with. First, for the 'business-as-usual' (BAU) scenario, temporal changes of economic system depicted by input-output tables could be considered (Zhao et al., 2017; Song et al., 2018; C. Li et al., 2021). Second, in the policy-related scenario, the reflection of multiple policy-related parameters in the multi-objective optimization models could be further explored. For example, carbon emissions have been found to be impacted by policy-related parameters, such as CO_2 emissions intensity target (Mi et al., 2017c), energy intensity target (Liu et al., 2022), energy consumption cap targets (Qi et al., 2020), and the share of non-fossil fuels in the total energy consumption (Zhou et al., 2012). But the impacts of these multiple policy-related parameters on CO_2 emissions have not been investigated. Finally, as for the problem-specific scenarios by multi-attribute decision making, although decision preferences are considered in form of the specification of weights under proper transformation functions (Parreiras and Vasconcelos, 2009; Yu et al., 2016b), the role of permutation and combination in specifying the potential scenarios could be emphasized (Yi et al., 2011). In this way, all the potential contexts are included since the number of external variables is not relatively large. At the same time, to fulfil the problem-specific objective, a multi-attribute importance method could be constructed. With this model, not only could the importance of each specified scenario be quantified, but the importance could also be allocated among sectors (Yi et al., 2011; Zhao et al., 2017).

As one application of input-output future scenarios, CO_2 emissions alleviation could be explored during the integration of IOA and scenarios analysis by way of MCDM, when considering the economy-energy-environment (3E) nexus (Dong et al., 2014; Carvalho et al., 2015; Rojas Sánchez et al., 2019; X. Li et al., 2021). CO_2 emissions alleviation in China is emphasized during the synergistic management of 3E nexus (S.-F. Zhang et al., 2019). China is in the process of industrialization and urbanization (two pillars of the economic development) (H. Wang et al., 2019), and needs to prioritize the long-term economic development (S.-F. Zhang et al., 2019). The demands for infrastructures and services will increase energy demand and CO_2 emissions (Li and Ouyang, 2021), which is especially the case when considering the coal-dominated energy structure difficult to reverse due to the constraints of energy use efficiency and clean technology (X. Zhang et al., 2017; F. Zhang et al., 2021). Then, it is also found that CO_2 emissions reduction in China tend to bring transformational pressures and challenges to economy and energy (S. Yu et al., 2018; B. Li et al., 2020; Li and Ouyang, 2021). In these regards, CO_2 emissions alleviation by exploring the 3E nexus is important and necessary.

Meanwhile, within the established 3E nexus framework, allocating CO_2 emissions reduction targets to each sector is an important way to complete carbon emissions reduction task (Zhao et al., 2017). During this allocation process, CO_2 emissions alleviation requires the synergies among sectors (Ning et al., 2019; Dong et al., 2023). The industrial synergistic development is characterised the interaction, independence and mutual support between sectors (Lin and Teng, 2023), which could be reflected by applying IOA and related input-output future scenarios (Yin et al., 2022). It is because IOA in the scenario context could manifest the flows of goods and services among sectors and demonstrate the sectoral interdependence within the economic structure (Jensen et al., 1988). However, despite that the importance of exploring the path of synergistic carbon emissions reduction of multiple sectors to improve carbon emission reduction efficiency has been recognized (Dong et al., 2023), previous studies have not conducted the exploration of sector-level CO_2 emissions synergistic alleviation. Also, the dynamics featuring the synergy of reducing CO_2 emissions among sectors has not been emphasized although the dynamical effects are supposed to be captured to facilitate CO_2 emissions abatement (M.-H. Jiang et al., 2021). To address these weaknesses, the overview of changes in CO_2 emissions is provided, and the direction and channels identifications are attained by means of the shift-share analysis (SSA).

Therefore, an integrated scheme of input-output future scenarios construction could be proposed to help alleviate CO_2 emissions in a holistic manner (Weng et al., 2010). That is, we set up three categories of input-output future scenarios by interconnecting production with consumption. In detail, we start the input-output BAU scenario by conducting a procedure of input-output forecasting on the basis of modified matrix transformation technique (MMTT). We then construct the input-output policy-related scenario by extending the multi-objective optimization method (MOOM) with multiple policy-related parameters to reflect the trade-offs of 3E system. We finally arrange input-output problem-specific scenarios using multi-attribute decision making (MADM) which incorporates the generalized weighting method with the permutation and combination method and supports the construction of a multi-attribute importance method. Within the constructed input-output future scenarios, sector-level CO_2 emissions synergistic alleviation is analysed through evaluating changes in CO_2 emissions in a holistic manner and with the SSA method. The study is in the case of China from 2020 to 2030. The remainder of this paper is organized as follows. Section 5.2 reviews the research concerning constructing interconnections between production and consumption within the input-output future scenarios for CO_2 emissions alleviation. Section 5.3 introduces the methodology and data. Section 5.4 is about results and discussion. Section 5.5 concludes this paper.

5.2. Literature review

Within the input-output future scenarios, BAU scenario is set as a reference to explore the impacts of influencing factors on external variables (Faber et al., 2007; X. Zhang et al., 2017; Ma et al., 2020), and thus subsequent scenario settings are formulated by incorporating specific elements (e.g., multiple objectives, multiple criteria) into the reference scenario (Chen et al., 2014; Oliveira et al., 2016; Ma et al., 2020). However, during the construction of input-output future scenarios, the interconnections between production and consumption have not been emphasized, despite that these interconnections fundamentally characterize the IOA scheme and related extensions to environment (Oliveira and Antunes, 2004; Weng et al., 2010; Carvalho et al., 2015; Oliveira et al., 2016; Rojas Sánchez et al., 2019).

To construct input-output future scenarios through the interconnections between production and consumption, some concerns need to be coped with, which include (1) how to start BAU scenario by considering the temporal changes of economic system depicted by input-output tables; (2) how to construct policy-related scenario by extending the multi-objective optimization method with multiple policy-related parameters for the trade-offs among multiple objectives; and (3) how to arrange problem-specific scenarios when traversing all the potential decision preferences among multiple attributes, and constructing a multi-attribute importance method to allocate importance among sectors are needed and feasible.

Regarding the construction of BAU scenario, RAS method is used to reflect the temporal changes of economic system depicted by input-output tables (Yu et al., 2016b; S.-W. Yu et al., 2018b). Despite the usefulness and efficiency, RAS method is mainly used for balancing the initial table (Wang et al., 2015a). Then, matrix transformation technique (MTT) is a method emphasizing economic structure changes over time by investigating a matrix-based economic structure (i.e., matrix-based links among intermediate input-outputs, final demand and value added) (Wang et al., 2015a). However, the weaknesses of MTT arise when (1) final demand signs are inconsistent between the prior table and the target table, (2) nonlinear interpolations are considered to reflect temporal changes, and (3) there is a need for depicting the propagation relationship between Ghosh model and the IOT-related models. In these regards, the modified MTT (MMTT) method realizes the following contents, including (1) probing into and then establishing a matrix-based economic structure (i.e., matrix-based links among intermediate input-outputs, final demand and value-added); (2) emphasizing economic structure changes over time; (3) adding up in the situation where the final demand signs are inconsistent between the prior table and the target table; (4) making sense regardless of whether the data assumptions are linear or nonlinear; (5) depicting the propagation relationship between Ghosh model and the IOT-related models; and (6) tracing structure changes of final demand and value added through the matrix-based linking method. Besides, the Fourier-Markov model is a mathematical technique for predicting the future values of a time series when the difference between the forecasts from basic models and initial estimates is taken into consideration (Lin et al., 2001; Su et al., 2002). This method has been conceived as a way of enhancing the accuracy of forecasting (Hsu et al., 2009). Thus, Fourier-Markov model could be combined with MMTT to construct the BAU scenario. But at the same time, the previous Fourier-Markov method cannot guarantee the accuracy of each observation, cannot ensure the constant good performance when compared with its original model that is based on, and will decrease the scope of application as its current form is not specified in a broad manner. Therefore, to address these weaknesses, we propose an element-based Fourier-Markov (EFM) method. Also, the EFM method could be applied regardless of whether the amount of data is large or not, which retains the advantages of the Fourier-Markov method (Lin et al., 2001; Su et al., 2002; Hsu et al., 2009). Besides, the EFM method could be used in the context of short- and long-term forecasting because the conversion matrix in the Markov process and the input parameters of the basic module of the Fourier-Markov method could be adjusted according to the changes in future trends (Alfieri et al., 2015; Z. Zhang et al., 2021; Rahnama, 2021). Then, BAU scenario could be validated by combining MMTT with Monte Carlo simulations (Wilting, 2012b), which provide more statistical information about the results.

The policy-related scenario could be constructed integrating IOA with the multi-objective optimization method. In the context of environment, CO_2 emissions alleviation is closely related to the trade-offs of 3E system (S.-F. Zhang et al., 2019; Ye et al., 2019; Ning et al., 2020), which has been explored in the multi-objective optimization context (Mi et al., 2015; S.-W. Yu et al., 2018b). At the same time, research on the influencing factors of CO_2 emissions has found that more policy-related parameters could be comprehended from the 3E nexus (Mao et al., 2014, 2021). These policy-related parameters include CO_2 emission intensity targets, energy intensity targets, energy consumption cap targets, and the share of non-fossil fuel in primary energy consumption (Zhou et al., 2012; Mi et al., 2017c; Qi et al., 2020; Liu et al., 2022). In this avenue, the multi-objective optimization method could be modified by including all of these parameters, so as to reflect the impacts of these parameters on CO_2 emissions reduction (Z.-Y. Li et al., 2021), and the trade-offs among 3E system (Mao et al., 2014). Also, this modification is supportive in the construction of input-output policy-related scenario through interconnecting production with consumption (Mao et al., 2014, 2021).

The problem-specific scenarios in terms of CO_2 emissions alleviation could be diverse, depending on how to reflect different decision preferences among multiple attributes when CO_2 emissions are allocated to sectors (Zhao et al., 2017). In this sense, the problem-specific scenarios could be arranged using the integration of IOA and multi-attribute decision making (MADM) methods (Yu et al., 2016b; S.-W. Yu et al., 2018b). In detail, to achieve the aggregate CO_2 emissions intensity target, some methods are proposed to transform this target into regional (Yi et al., 2011; Zhang et al., 2014) or sectoral endeavours (Zhao et al., 2017). These researches emphasize the importance of allocating CO_2 emissions from the perspective of production-based CO_2 emissions accounting. Then, although more studies support the necessity of analysing sector-level impacts on CO_2 emissions reduction (Zhao et al., 2017; Song et al., 2018; Chen et al., 2020; W.-H. Xu et al., 2021; Fang et al., 2022), current input-output future scenarios have not considered the role of sector-level CO_2 emissions intensities in CO_2 emissions alleviation (Matsumoto et al., 2019). That is, the sector-level CO_2 emissions intensities are forecasted, rather than considered as the additional directions towards CO_2 emissions alleviation (Ouyang and Lin, 2015; Zhao et al., 2017; Chen et al., 2020). For example, the energy intensity targets have been proposed for energy-intensive sectors for energy conservation and CO_2 emissions reduction in China (Ouyang and Lin, 2015; Chen et al., 2020). In these regards, the problem-specific scenarios could be arranged as the third category of input-output future scenarios by integrating IOA with MADM by proposing a multi-attribute importance method (Yi et al., 2011; Zhao et al., 2017). This is also an aspect of interconnecting production with consumption (Oliveira et al., 2016; Rojas Sánchez et al., 2019). Besides, to arrange problem-specific scenarios, different decision preferences need to be specified among multiple criteria (Zhao et al., 2017). During this process, although traversing all the potential decision preferences is needed and feasible, current studies have not included the whole set of decision preferences. As such, when specifying all the potential decision preferences, the generalized weighting method (Zhang et al., 2004) in relation to permutation and combination is proposed (Yi et al., 2011; Yu et al., 2016b).

With the established input-output future scenarios, CO_2 emissions synergistic alleviation could be further achieved not only through analysing the overview of changes in CO_2 emissions, but also through evaluating CO_2 emissions changes with shift-share analysis (SSA). SSA is a technique that focuses on partitioning the growth in an economic variable in a particular area into various components when considering the changes in the variable as a dynamic progress (Creamer, 1943; Yavas et al., 1992; Lin et al., 2019). This growth is decomposed into national growth, industrial mix, and competitive position effects. Thus, with the SSA method, the determinants of growth and decline could be figured out. Also, this method enables to identify the key sectors which contribute to the changes in variables and to grasp both the direction about how the future develops as well as the principle of adjusting industrial structure.

However, due to the existence of interwoven effect in industrial mix and competitive position effects, the Esteban-Marquillas version of SSA is proposed by introducing homothetic variables to deal with component independence (Esteban-Marquillas, 1972; Sheng et al., 2021). Also, when SSA is used as a comparative static approach, which considers conditions only at the beginning and end years of the time period, the SSA method influences the allocation of changes in variables among the three shift-share effects (Barff and Iii, 1988). Thus, the dynamics is introduced to the Esteban-Marquillas shift-share extension. But at the same time, when it comes to the application of this dynamic Esteban-Marquillas method to evaluating changes in CO_2 emissions, previous studies have not taken this aspect into consideration although the SSA method has been used in diverse fields, including economy, energy and environment (Li and Huang, 2010; H. Li et al., 2017; Lin et al., 2019).

Based on the previous studies, we propose an integrated scheme of input-output future scenarios construction to help alleviate CO_2 emissions in a holistic manner. That is, we set up three categories of input-output future scenarios by interconnecting production with consumption. In detail, we start the input-output BAU scenario by conducting a procedure of input-output forecasting on the basis of the EFM method, MMTT and Monte Carlo simulation. Then, we construct the input-output policy-related scenario by extending the multi-objective optimization method with multiple policy-related parameters. Finally, we arrange the input-output problem-specific scenarios using multi-criteria decision making which incorporates the generalized weighting method with the permutation and combination method, and supports the construction of a multi-attribute importance method. With the three constructed categories of input-output scenarios, sector-level CO_2 emissions synergistic alleviation is analysed through the overview of changes in CO_2 emissions and the application of SSA to direction and channel identifications when evaluating CO_2 emissions changes.

5.3. Method and data

5.3.1. BAU scenario: Conducting the procedure of input-output forecasting

To start the input-output BAU scenario, a procedure of input-output forecasting is conducted, which includes (1) input-output forecasts, (2) input-output forecasts structuring, and (3) input-output forecasts validation, and is expressed as follows.

5.3.1.1. Input-output forecasts

To trace the trends inherent in the economic system, the element-based Fourier-Markov (EFM) method is proposed. To explain the EFM method, we start with the modified Fourier correction (MFC) method with basic module. Then, we introduce the Markov process to the MFC method. Because the performance of EFM method with typical sequences has been evaluated in Chapter 4, the performance evaluation of EFM method is not included in Chapter 5.

5.3.1.1.1. The MFC method with basic module

The moving average (MA) method is used as the basic module for EFM method because MA method could track both linear and nonlinear changes in time series data (Xiong et al., 2011). The MA method is explained as follows (Hansun, 2013).

$$M_t = M_{t-1} + (y_t - y_{t-n})/n \qquad (5-1)$$

where M_t is the prediction at time t, M_{t-1} is the predicted values at time $t-1$, y_t is the data point value at time t, y_{t-n} is the data point value at time $\mathrm{t}-n$, and n is the number of data points used in the calculation.

Then, the MFC approach is to increase prediction capacity from the considered input data sets. Compared with the previous use of Fourier series, this study proposes four improvements: the first one is using the quotient form of residual series to maintain the consistency between initial estimates and predictions, the second is extending the application of Fourier series to both odd and even cases (Smith, 1999; Selesnick and Schuller, 2000), the third is using the singular value decomposition (SVD) to attain the coefficients of Fourier series, and the fourth is integrating the mechanism where each element gets considered into the Fourier correction. Thus, the MFC method is explained as follows.

$$\boldsymbol{E_r} = \{E_r(1), E_r(2), \cdots, E_r(q)\}^T \qquad (5-2)$$

where E_r is the quotient form of the residuals series, and

$$E_r(k) = y_k/\hat{y}_k, k = 1, 2, \cdots, q \qquad (5-3)$$

Then, the Fourier series can approximate the quotient form of residual series as follows.

$$E_r(k) = \frac{1}{2}a_0 + \sum_{i=1}^{ka}\left[a_i\, cos\left(\frac{i \cdot 2\pi}{T}k\right) + b_i\, sin\left(\frac{i \cdot 2\pi}{T}k\right)\right], k = 1, 2, \cdots, q \qquad (5-4)$$

where $T = q$, and

$$k_a = \begin{cases} \dfrac{q}{2} + 1, if\ \ q\ \ is\ \ even \\ \dfrac{(q-1)}{2} + 1, if\ \ q\ \ is\ \ odd \end{cases} \qquad (5-5)$$

The coefficients derived from the Fourier correction approach (i.e., $Q = [a_0, a_1, b_1, a_2, b_2, \cdots, a_{ka}, b_{ka}]^T$), are calculated as follows.

$$\boldsymbol{Q} = \boldsymbol{P}^{\dagger}\boldsymbol{E_r} \qquad (5-6)$$

where $\boldsymbol{P}^{\dagger}$ is the Moore-Penrose pseudo-inverse of $\boldsymbol{P}$ as follows.

$$\boldsymbol{P} = \begin{bmatrix} \frac{1}{2} & cos\left(\frac{2\pi\cdot 2}{T}\right) & sin\left(\frac{2\pi\cdot 2}{T}\right) & cos\left(\frac{2\pi\cdot 2\cdot 2}{T}\right) & sin\left(\frac{2\pi\cdot 2\cdot 2}{T}\right) & \cdots & cos\left(\frac{k_a\cdot 2\pi\cdot 2}{T}\right) & sin\left(\frac{k_a\cdot 2\pi\cdot 2}{T}\right) \\ \frac{1}{2} & cos\left(\frac{2\pi\cdot 3}{T}\right) & sin\left(\frac{2\pi\cdot 3}{T}\right) & cos\left(\frac{2\pi\cdot 2\cdot 3}{T}\right) & sin\left(\frac{2\pi\cdot 2\cdot 3}{T}\right) & \cdots & cos\left(\frac{k_a\cdot 2\pi\cdot 3}{T}\right) & sin\left(\frac{k_a\cdot 2\pi\cdot 3}{T}\right) \\ & & & & \vdots & & & \\ \frac{1}{2} & cos\left(\frac{2\pi\cdot q}{T}\right) & sin\left(\frac{2\pi\cdot q}{T}\right) & cos\left(\frac{2\pi\cdot 2\cdot q}{T}\right) & sin\left(\frac{2\pi\cdot 2\cdot q}{T}\right) & \cdots & cos\left(\frac{k_a\cdot 2\pi\cdot q}{T}\right) & sin\left(\frac{k_a\cdot 2\pi\cdot q}{T}\right) \end{bmatrix} (5-7)$$

The original prediction series can be corrected as follows.

$$\widehat{M_k} = M_k \times E_r(k), k = 1, 2, \cdots, q \qquad (5-8)$$

5.3.1.1.2. The establishment of EFM method

The MFC method could be adjusted when there are occurred events in future (Lin et al., 2001; Hsu et al., 2009). To achieve this, the Markov process is introduced on the basis of the MFC approach. With this improvement, the new mechanism where the impact of each element on the prediction is integrated into the Fourier-Markov method, the constant good performance when compared with its original model based on is ensured, and the scope of application is complete when its current form is specified in a broad manner. This is what we have termed an element-based Fourier-Markov (EFM) method. The following is the process about how the EFM method operates.

Similar to the MFC method in Section 5.3.1.1.1, the EFM method uses the quotient form of residual series to maintain the consistency between initial estimates and predictions. The residual errors are portioned into r equal portions called states. Each state is an interval whose width is equal to a fixed portion of the range between the maximum and the minimum of the whole residual error (Li et al., 2007). Let S_j be the jth state.

$$S_j \in [SL_j, SU_j], j = 1, 2, \cdots, r \qquad (5-9)$$

where SL_j and SU_j are the lower and upper boundary of the jth state, and r is the integer portion of $ln(n)/ln\,2$.

$$SL_{tj} = \min_t e(t) + \frac{j-1}{r}\left(\max_t e(t) - \min_t e(t)\right) \qquad (5-10)$$

$$SU_{tj} = \min_t e(t) + \frac{j}{r}\left(\max_t e(t) - \min_t e(t)\right) \qquad (5-11)$$

where $e(t)$ is the quotient form of the residual error of the MFC method, $t = 1, 2, \cdots, q$, and $j = 1, 2, \cdots, r$.

Let $P_{ij}^{(m)}$ be the transition probability from the ith state to the jth state by m steps.

$$P_{ij}^{(m)} = \frac{R_{ij}^{(m)}}{R_i}, j = 1, 2, \cdots, r \qquad (5-12)$$

where $R_{ij}^{(m)}$ is the transition times that occurred from state i to j by m steps, and R_i is the number of data belonging to the ith state.

Let $Q_t^{(m)} = \left(P_{t1}^{(m)}, P_{t2}^{(m)}, \cdots, P_{tr}^{(m)}\right)$ be the row vector of transition probabilities of ith state at m time steps. The center vector of each state is denoted by $v = \left(v(1), v(2), \cdots, v(r)\right)$, with $v(j) = \sigma \times SL_j + (1-\sigma) \times SU_j$.

The adjusted prediction, $\widehat{M_t^{(a)}}$, in the EFM method is given by

$$\widehat{M_t^{(a)}} = \widehat{M_t} \times Q_t^{(m)} v(j) \qquad (5-13)$$

5.3.1.2. Input-output forecasts structuring

For completing the structuring of input-output forecasts, the process goes through two steps. The first is concerned with proposing MMTT to structure input-output forecasts. The second is about extending MMTT by a matrix-based linking method to structure the final demand and value-added categories.

Matrix transpose is used to modify MTT, which ensures that the modified MTT (MMTT) is still a matrix calculation method emphasizing structural changes but overcomes the three possible weaknesses of MTT (as introduced in Section 5.2). Through the MMTT method, new matrix-based links among intermediate input-outputs, final demand and value added are established. Related equations are as follows.

The initial matrix input, $\boldsymbol{X_0}$, is an $(n+1)\times(n+1)$ matrix.

$$\boldsymbol{X_0} = \begin{bmatrix} \boldsymbol{D}_0 & \boldsymbol{F}_0 \\ \boldsymbol{V}_0 & \boldsymbol{G}_0 \end{bmatrix} \qquad (5-14)$$

where $\boldsymbol{D_0}$ is an $n \times n$ matrix depicting intermediate input-outputs among n sectors, $\boldsymbol{F_0}$ represents an $n \times 1$ matrix denoting final demand, $\boldsymbol{V_0}$ is a $1 \times n$ matrix representing sector-level value added, and $\boldsymbol{G_0}$ is the total final demand.

We convert $\boldsymbol{X_0}$ into $\boldsymbol{Y}$ and then transpose $\boldsymbol{Y}$ as follows.

$$\boldsymbol{Y} = \begin{bmatrix} \boldsymbol{d} & \boldsymbol{v} \\ \boldsymbol{f} & \boldsymbol{g} \end{bmatrix} \qquad (5-15)$$

where $\boldsymbol{d} = \left(\widehat{\boldsymbol{V_0}}\right)^{-1}\boldsymbol{D_0}$ denoting the forecast of $\boldsymbol{d}$ based on the EFM method, $\boldsymbol{v}$ is an $n \times 1$ matrix with each element being one, $\boldsymbol{f} = \left(\widehat{\boldsymbol{G_0}}\right)^{-1}\boldsymbol{F_0}$, $\boldsymbol{g}$ equals one and ^ represents diagonalization of the vector.

$$\boldsymbol{N} = diag\left(1 - \sum_{i}^{n} d_{1i}, 1 - \sum_{i}^{n} d_{2i}, \cdots, 1 - \sum_{i}^{n} d_{ni}\right) + \boldsymbol{d}^{\boldsymbol{T}} \qquad (5-16)$$

$$\boldsymbol{F_1} = \boldsymbol{N}\boldsymbol{V_1} \qquad (5-17)$$

$$\boldsymbol{D_1} = \widehat{\boldsymbol{V_1}}\boldsymbol{d} \qquad (5-18)$$

$$\boldsymbol{G_1} = \sum \boldsymbol{F_1} \qquad (5-19)$$

where $\boldsymbol{D_1}$ $\boldsymbol{F_1}$, $\boldsymbol{V_1}$ and $\boldsymbol{G_1}$ are the forecast of intermediate input-outputs, the forecast of final demand, the forecast of value added, and the forecast of total final demand respectively. Correspondingly, $\boldsymbol{X_1}$ is the structuring of input-output forecasts.

$$\boldsymbol{X_1} = \begin{bmatrix} \boldsymbol{D_1} & \boldsymbol{F_1} \\ \boldsymbol{V_1} & \boldsymbol{G_1} \end{bmatrix} \qquad (5-20)$$

In terms of unfolding the forecasts of both the final demand and value-added, the MMTT method is further extended with a matrix-based linking method. First, the matrix-based linking method starts from the final demand and value added derived from the results of the MMTT method. Since this linking method is matrix-based, the links between the categories of final demand (or value added) and intermediate input-outputs are established in a direct and deterministic manner. Then, this matrix-based linking method investigates and then establishes the matrix-based structures of final demand (or value added), allowing positive and negative categories of final demand (or value added). Subsequently, the exact temporal impacts of each element of final demand and value added are calculated; meanwhile, the matrix-based structures are consistent with the results from the MMTT method. The characteristics of this matrix-based linking method include achieving automatic and straightforward adjustments when capturing and linking structure changes, and reflecting linear and/or non-linear impacts over time. Related equations are as follows.

$$\boldsymbol{U_{category}} = \begin{cases} \widehat{\boldsymbol{u_c}}\widehat{\boldsymbol{U_c}}\boldsymbol{u_n^*}(\widehat{\boldsymbol{u_n}})^{-1} & \boldsymbol{if} \ \ \boldsymbol{u_n} \neq \boldsymbol{0} \\ \widehat{\boldsymbol{u_c}}\boldsymbol{w_m}\boldsymbol{w_n} & \boldsymbol{if} \ \ \boldsymbol{u_n} = \boldsymbol{0} \end{cases} \quad (5-21)$$

$$\boldsymbol{U_c} = \left[\boldsymbol{U_c^p}, \boldsymbol{U_c^n}\right] \quad (5-22)$$

$$\boldsymbol{u_c} = \begin{bmatrix} \boldsymbol{u_p^d} \\ \boldsymbol{u_n^d} \end{bmatrix} \quad (5-23)$$

$$\boldsymbol{w_n} = \begin{bmatrix} \boldsymbol{u_m} \\ \boldsymbol{u_n^*} \end{bmatrix} \quad (5-24)$$

where $\boldsymbol{U_{category}}$ denote the categories of final demand (or value added) on the basis of the MMTT method and the matrix-based linking method, $\boldsymbol{u_n^*}$ is the vector for the sum of positive and negative values of final demand (or value added) updated by the MMTT method, $\boldsymbol{u_n}$ is the vector for the sum of positive and negative values of final demand (or value added) to update, $\boldsymbol{u_m}$ is the vector for the difference of positive and negative values of final demand (or value added) to update, $\boldsymbol{U_c^p}$ is the vector for the sum of positive values of final demand (or value added) to update, $\boldsymbol{U_c^n}$ is the vector for the sum of negative values of final demand (or value added) to update, $\boldsymbol{u_p^d}$ is the vector for the updated share of each positive final demand (or value added) category in total positive final demand (or value added), $\boldsymbol{u_n^d}$ is the vector for the updated share of each negative final demand (or value added) category in total final demand (or value added), and the new elements added at the end of $\boldsymbol{u_p^d}$ ($\boldsymbol{u_n^d}$) are zeros to form the complete $\boldsymbol{u_p^d}$ ($\boldsymbol{u_n^d}$) when the dimensions of $\boldsymbol{u_p^d}$ and $\boldsymbol{u_n^d}$ are different.

Then, $\boldsymbol{w_m}$ is calculated as follows.

$$\boldsymbol{w_m}\boldsymbol{w_n} = \boldsymbol{w^{-1}}\boldsymbol{w_n} \quad (5-25)$$

where $\boldsymbol{w}$ is the matrix $\begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}$.

The constructed IOTs need to be converted to noncompetitive IOTs by quantifying the impacts of imports on IOTs. Following the study (Su and Ang, 2013), the impacts of imports are distributed proportionally to the intermediate input-outputs and final demand categories, which is based on the import ratios as follows.

$$\boldsymbol{M} = \mathrm{diag}\left(\left(\mathbf{D_1} + \mathbf{F_{category}} + \mathbf{IM} - \mathbf{EX}\right)^{-1}\right)\widehat{\mathbf{IM}} \qquad (5-26)$$

where $\boldsymbol{M}$ is an $n \times n$ matrix denoting the import ratios, $\boldsymbol{F_{category}}$ are final demand categories, $\boldsymbol{IM}$ are imports, and $\boldsymbol{EX}$ are exports.

5.3.1.3. Input-output forecasts validation

For validating one forecasted input-output table (IOT), the process is achieved by the combination of MMTT, which is introduced in Section 3.1.2, with Monte Carlo simulations. The uncertainty is measured by using the 2.5th and 97.5th percentiles of the data (Lu et al., 2011; Pinder et al., 2012; Lauerwald et al., 2015; Su et al., 2015; Ayarzagüena et al., 2020), which represent the upper and lower bounds respectively. To compare the variations in the uncertainty over time, a Z-score measurement (i.e., a value minus the population mean, divided by the population standard deviation) is needed. This measurement describes a value’s relation to the mean of the data (i.e., a group of values) and is used to compared different datasets.

5.3.2. Policy-related scenario: Extending multi-objective optimization model

To construct the input-output policy-related scenario, MOOM is extended by including multiple policy-related parameters, so as to reflect the trade-offs among 3E system. The policy-related scenario construction consists of (1) objectives, (2) constraints, (3) policy-related parameters, (4) optimization algorithm, and (5) solution selection, which is expressed as follows.

5.3.2.1. Objectives

The objective functions include (1) maximization of the gross domestic product (GDP), (2) minimization of energy consumption, (3) minimization of CO_2 emissions, and (4) minimization based on input-output balance constraints, which are expressed as follows.

$$max\, f_1 = \sum \boldsymbol{X_t}(\boldsymbol{I} - \boldsymbol{A_t}) \tag{5-27}$$

where f_1 is the total value of GDP, $\boldsymbol{X_t}$ is the sector-level output in the tth year, and $\boldsymbol{A_t}$ is the direct consumption coefficient matrix in tth year.

$$min\, f_2 = \sum \boldsymbol{e_t}\boldsymbol{X_t} \tag{5-28}$$

where f_2 is the total energy consumption, and $\boldsymbol{e_t}$ is the energy consumption per unit of total output of each sector in tth year.

$$min\, f_3 = \sum \boldsymbol{c_t}\boldsymbol{X_t} \tag{5-29}$$

where f_3 is the total CO_2 emissions, and $\boldsymbol{c_t}$ is the CO_2 emissions per unit of total output of each sector in tth year.

$$\boldsymbol{min\, f_i = X_t - X_t A_t - Q_t(X_t - X_{t-1}) - Y_t} \tag{5-30}$$

where $\boldsymbol{f_i}$ is the dynamic input-output balance for each sector i, $\boldsymbol{Q_t}$ is the investment coefficient matrix in the tth year, and $\boldsymbol{Y_t}$ is the final consumption and export of sector i in tth year.

5.3.2.2. Constraints

The constraints of MOOM include (1) energy intensity constraints, (2) CO_2 emissions intensity constraints, (3) non-fossil fuel consumption constraints, (4) energy consumption constraints, and (5) nonnegative constraints. The constraints are expressed as follows.

$$\left(E_t/\sum \boldsymbol{X_t}(\boldsymbol{1}-\boldsymbol{A_t})\right)/\left(E_{t-1}/\sum \boldsymbol{X_{t-1}}(\boldsymbol{1}-\boldsymbol{A_{t-1}})\right) \le 1-\alpha_t \qquad (5-31)$$

where E_t is the total energy consumption in tth year, and α_t is the energy intensity reduction rate in tth year.

$$\left(C_t/\sum \boldsymbol{X_t}(\boldsymbol{1}-\boldsymbol{A_t})\right)/\left(C_{t-1}/\sum \boldsymbol{X_{t-1}}(\boldsymbol{1}-\boldsymbol{A_{t-1}})\right) \le 1-\beta_t \qquad (5-32)$$

where C_t is the total CO_2 emissions in tth year, and β_t is the carbon intensity reduction rate in tth year.

$$NE_t \le E_t \times \delta_t + RE_t \qquad (5-33)$$

where NE_t is the total non-fossil energy consumption in tth year, δ_t is the shares of non-fossil fuels in the total energy consumption in tth year, and $\mathrm{RE_t}$ is the residential energy consumption in the tth year.

$$\sum \boldsymbol{e_t X_t} \le E_{cap,t} \qquad (5-34)$$

where $E_{cap,t}$ is the energy consumption cap target in the tth year.

$$\boldsymbol{X_t} \ge \boldsymbol{0} \qquad (5-35)$$

where $\boldsymbol{X_t} \ge \boldsymbol{0}$ is set to ensure the practical significance of the decision variables.

5.3.2.3. Policy-related parameters

The policy-related parameters used in the constraints are explained as follows. In detail, α_t and β_t are based on *the Outline of China's 14th Five-Year Plan (2021-2025) for National Economic and Social Development and the Long-Range Objectives Trough the Year 2035* (NPC, 2021). That is, energy consumption per unit of gross domestic product (GDP) and carbon dioxide emissions per unit of GDP will be reduced by 13.5% and 18%, respectively. E_t is calculated according to the target from *National Strategy on Energy Production and Consumption Revolution (2016-2030)* (i.e., the amount of energy consumption by 2030 is set to be 6 Gtce) (NDRC, 2016). δ_t is calculated according to the target from *Action Plan for Carbon Dioxide Peaking Before 2030* (i.e., the shares of non-fossil fuels in total energy consumption will reach around 20% by 2025 and 25% by 2030 respectively) (The State Council, 2021).

5.3.2.4. Optimization algorithm

Multi-objective optimization allows for generating a Pareto solution set, rather than a single solution (Yu et al., 2016b), which supports the decision making with regard to the consideration of different preferences (Dai et al., 2017). The NSGA-II (non-dominated sorting genetic algorithm) achieves the low computation complexity through the fast non-dominated sorting approach (Deb et al., 2002), and maintains the diversity of solutions by way of the crowding distance estimation and a crowded comparison operator (Deb et al., 2002). In these regards, the NSGA-II algorithm has been widely used in various fields, such as economy (X.-H. Wang et al., 2018), energy (Yu et al., 2016b), and environment (Y.-H. Wang et al., 2020).

5.3.2.5. Final solution selection method

For selecting the trade-off solution from the Pareto front of MOOM, we specify the weights (Zhang et al., 2004) and then apply the multi-criteria tournament decision (MTD) (Parreiras and Vasconcelos, 2009). Additionally, the specification of weights is also among MCDM techniques. The weights are specified as follows.

$$w_j = \left(\prod_{l=1}^{n} p_{jl}\right)^{1/n} \qquad (5-36)$$

where w_j is the weight of indicator j, $p_{jl} = 9^{u_j - u_l}$ ($j, l = 1, \dots, n$), $u_i = (n - o_j)/(n-1)$, $u_j = (n - o_l)/(n-1)$, and o_j and o_l is the position of the jth and the lth criteria in the ordering proposed. In addition, the weights are normalized in such way that $\sum_{j=1}^{n} w_j = 1$.

Then, MTD is applied to select the trade-off solution from the Pareto front, which is explained as follows (Parreiras and Vasconcelos, 2009).

$$Q_j(a, A) = \sum_{\forall b \in A \wedge a \neq b} \frac{q_j(a, b)}{(|A| - 1)} \qquad (5-37)$$

$$R(a) = \left(\prod_{j}^{m} Q_j(a, A)^{w_j}\right)^{\frac{1}{m}} \qquad (5-38)$$

$$R(a) = min\{Q_j(a, A)^{w_1}, \quad \cdots, \quad Q_j(a, A)^{w_m}\} \qquad (5-39)$$

where $q_i(a, b)$ is defined as $q_i(a, b) = \begin{cases} 1, & if \;\; f_i(\vec{x}_b) - f_i(\vec{x}_a) > 0 \\ 0, & if \;\; f_i(\vec{x}_b) - f_i(\vec{x}_a) \leq 0 \end{cases}$, and $f_i(\cdot)$ is the fitness function employed in MOOM.

5.3.3. Problem-specific scenarios: Proposing a multi-attribute importance method

To make multi-attribute decisions regarding carbon intensity reduction allocation among sectors in the context of problem-specific scenarios, there are three steps for a multi-attribute importance method proposed in this section. First, the indicators, as the criteria, are collected to form a decision making matrix. Second, the multi-attribute importance in different scenarios is calculated. Lastly, a multi-attribute importance method is utilized at the sector level for carbon intensity reduction allocation within different scenarios. With this procedure, the problem-specific scenarios are constructed.

5.3.3.1. Sector-level indicators collection

The indicators are collected in terms of capacity, responsibility and potential (Yi et al., 2011; Zhao et al., 2017). These indicators are sector-level value-added, sector-level cumulative CO_2 emissions, and sector-level energy consumption per unit of value added.

The decision making matrix $\boldsymbol{N}$ of n indicators for m sectors is explained as follows.

$$\boldsymbol{N} = \begin{bmatrix} n_{11} & \cdots & n_{1n} \\ \vdots & \ddots & \vdots \\ n_{m1} & \cdots & n_{mn} \end{bmatrix} \qquad (5-40)$$

where n_{ij} is the value of indicator j for sector i ($i = 1,2,\cdots,\mathrm{m}$; $j = 1,2,\cdots,\mathrm{n}$).

The indicators selected are normalized, according to a larger value of a positive indicator indicating the better performance while a smaller value of a negative indicator indicating the better performance (Mi et al., 2017b; Shen et al., 2021). Then, the normalization of n_{ij} is expressed as follows.

$$z_{ij} = \left(n_{ij} - n_{ij}^{min}\right) / \left(n_{ij}^{max} - n_{ij}^{min}\right) \qquad (5-41)$$

$$z_{ij} = \left(n_{ij}^{max} - n_{ij}\right) / \left(n_{ij}^{max} - n_{ij}^{min}\right) \qquad (5-42)$$

where z_{ij} is the normalized value of n_{ij}, $n_{ij}^{min} = \min_i n_{ij}$, and $n_{ij}^{max} = \max_i n_{ij}$.

5.3.3.2. Importance calculation in different scenarios

Importance in different scenarios is calculated by weights classified into three categories, so as to reflect different scenarios. The weights are composed of (1) weights under BAU scenario (Lin et al., 2001; Hsu et al., 2009), (2) objective weights based on entropy weighting method (Zhang et al., 2014; Shen et al., 2021), and (3) subjective weights based on the integration of the generalized weighting method (Zhang et al., 2004) and the permutation and combination method (Yi et al., 2011; Yu et al., 2016b).

The methods for three categories of weights are expressed as follows. First, weights under BAU scenario are calculated using the EFM method which is introduced in Section 5.3.1.1. Second, objective weights are calculated on the basis of the entropy weighting method. The information entropy measures the disorder degree of a system (Chang and Chang, 2016). The small information entropy indicates the great impact on the comprehensive assessment and the great entropy weight (Y.-Y. Zhang et al., 2020). The weighting method based on the information entropy has been widely utilized in various fields, such as economy (X.-F. Liu et al., 2019), energy (Lin and Zhou, 2022), and environment (Zhao et al., 2017), which is expressed as follows.

$$w_j = (1 - h_j) / \sum_{j=1}^{n} (1 - h_j) \qquad (5-43)$$

$$h_j = -(\ln m)^{-1} \sum_{i=1}^{m} d_{ij} \ln d_{ij} \qquad (5-44)$$

$$d_{ij} = z_{ij} / \sum_{i=1}^{m} z_{ij} \qquad (5-45)$$

where w_j is the entropy weight of indicator j, and h_j is the entropy of indicator j.

Third, subjective weights are derived from the scenario settings on the basis of the permutation and combination method. To be specific, according to the indicators collected, the related scenarios are set up, depending on the different preference towards capacity, responsibility and potential (Weng et al., 2010; Yi et al., 2011; Yu et al., 2016b). The number of the scenarios in terms of these three indicators is $(3! + 7)$, which is explained in Table 5-1. In Table 5-1, the contexts are for depicting the preference-oriented portfolio, so some contexts are repeated under different preferences. For example, the first context under capacity preference is the same as the first context under responsibility preference. Then, according to Table 5-1, subjective weights are calculated through the generalized weighting method (Zhang et al., 2004) which is introduced in Section 5.3.2.5.

Table 5-1 Decision preferences among capacity, responsibility and potential

Preference	Contexts	Criteria ranking
	$fit_1 \approx fit_2 \succ fit_3$	(1,1,2)
	$fit_1 \approx fit_3 \succ fit_2$	(1,2,1)
Capacity (fit_1)	$fit_1 \succ fit_2 \approx fit_3$	(1,2,2)
	$fit_1 \succ fit_2 \succ fit_3$	(1,2,3)
	$fit_1 \succ fit_3 \succ fit_2$	(1,3,2)
	$fit_1 \approx fit_2 \succ fit_3$	(1,1,2)
	$fit_2 \approx fit_3 \succ fit_1$	(2,1,1)
Responsibility (fit_2)	$fit_2 \succ fit_1 \approx fit_3$	(2,1,2)
	$fit_2 \succ fit_1 \succ fit_3$	(2,1,3)
	$fit_2 \succ fit_3 \succ fit_1$	(3,1,2)
	$fit_1 \approx fit_3 \succ fit_2$	(1,2,1)
	$fit_2 \approx fit_3 \succ fit_1$	(2,1,1)
Potential (fit_3)	$fit_3 \succ fit_1 \approx fit_2$	(2,2,1)
	$fit_3 \succ fit_1 \succ fit_2$	(2,3,1)
	$fit_3 \succ fit_2 \succ fit_1$	(3,2,1)
Equality	$fit_1 \approx fit_2 \approx fit_3$	(1,1,1)

Note: $fit_1 \succ fit_2$ means that fit_1 is strictly more important than fit_2, and $fit_1 \approx fit_2$ means that fit_1 is as important as fit_2.

5.3.3.3. Carbon intensity reduction allocation among sectors

The simultaneous consideration of diverse planning-based parameters is as follows.

$$C_t = E_l Z_l (1 - (t - l)\beta)(1 + \gamma)^{(t-l)} \qquad (5-46)$$

where C_t is the CO_2 emissions in year t, E_l is the CO_2 intensity in year l, Z_l is the GDP in year l, β is the average reduction rate of CO_2 emission intensity, and γ is the average growth rate of GDP.

According to planning-based parameters in terms of economy and CO_2 emissions, the optimum situation for attaining the growth rate of GDP is as follows.

$$\gamma_{opt} = exp(\beta/(1 - (t - l)\beta)) - 1 \qquad (5-47)$$

where γ_{opt} is the optimum growth rate of GDP when the planning-based parameters in light of economy and CO_2 emissions are considered.

Then, when planning-based parameters in terms of energy consumption are considered, the optimum situation of attaining the growth rate of GDP is adjusted as follows.

$$\gamma'_{opt} = \sqrt[(t-l)]{E_{cap,t}/f_l Z_l (1 - (t - l)\alpha)} - 1 \qquad (5-48)$$

where γ'_{opt} is the adjusted growth rate of GDP, f_l is the energy intensity in year l, and α is the average reduction rate of energy intensity.

Subsequently, the reduction rate of CO_2 emissions for each year could be obtained as follows.

$$\theta_t = (1 - (t - l) \times \beta) \times \left(1 + \gamma'_{opt}\right)^t - 1 \qquad (5-49)$$

where θ_t is the reduction rate of CO_2 emissions in the tth year.

To quantify the multi-attribute importance at sector level, the weighted sum model is used because of its straightforward adaptability and wide applicability (Yi et al., 2011; Shen et al., 2021; R.-L. Sun et al., 2020).

$$k_i = \sum_{j=1}^{n} w_j z_{ij} \qquad (5-50)$$

where k_i is the composite index of sector i.

The larger the value of the composite index is, the larger the carbon intensity reduction is (Yi et al., 2011; Zhao et al., 2017), which is further developed for sector-level allocation by proposing a multi-attribute importance method. For this method, CO_2 intensity changing coefficient is newly defined. This result of CO_2 intensity changing coefficient calculation is used for comparing the different scenarios and identifying the feasible scenarios. That is, the large value of CO_2 intensity changing coefficient indicates the more difficulty of reducing CO_2 emissions and then the low feasibility of this sort of scenario.

$$\varphi_t = (C_{t-1} \times \theta_t) / \sum \left(k_i \times \mu_{t-1} \times \sum \boldsymbol{X_t}(\boldsymbol{I} - \boldsymbol{A_t})\right) \qquad (5-51)$$

where φ_t is the CO_2 intensity changing coefficient in tth year, and μ_{t-1} is the sectoral carbon intensity in $(t-1)$th year.

$$\varphi_i = \left(\tau_{t-1} + \varphi_t k_i \times \mu_{t-1} \times \sum \boldsymbol{X_t}(\boldsymbol{I} - \boldsymbol{A_t})\right) / \sum \boldsymbol{X_t}(\boldsymbol{I} - \boldsymbol{A_t}) \qquad (5-52)$$

where φ_i is the CO_2 emissions intensity of sector i, and τ_{t-1} is the sectoral CO_2 emissions in $(t-1)$th year.

5.3.4. Evaluating changes in CO_2 emissions

To evaluate changes in CO_2 emissions for promoting CO_2 emissions synergistic alleviation, this study proceeds with the overview of and disaggregate-level related changes. The former is demonstrated by using the feasibility of CO_2 emissions reduction, and the structure changes, sectoral changes and peak year of CO_2 emissions. The latter is achieved with the extended shift-share analysis (SSA) which refers to the dynamic Esteban-Marquillas version of SSA. What follows is the process of applying the Esteban-Marquillas shift-share method to evaluate changes in CO_2 emissions.

In the Esteban-Marquillas shift-share analysis, the absolute changes of CO_2 emissions can be expressed as follows.

$$S_{ij} = NS_{ij} + IS_{ij} + CS_{ij} + AS_{ij} \qquad (5-53)$$

where NS_{ij} is the area-wide effect of sector j in the studied area i, IS_{ij} is the industry-mix effect of sector j in the studied area i, CS_{ij} is the competitive effect sector j in the studied area i, and AS_{ij} is the allocation effect of sector j in the studied area i. Because the term area can refer to any special unit (Borozan, 2018), in this study, the reference area denotes the average level of CO_2 emissions at the national level and the studied area denotes the individual level of CO_2 emissions across all sectors. Then, the four components of S_{ij} are explained using the following formulas.

$$NS_{ij} = \sum_{t=1}^{k} e_{ij}^{(0)} \frac{E^{(t)} - E^{(t-1)}}{E^{(0)}} \qquad (5-54)$$

where $e_{ij}^{(0)}$ is the CO_2 emissions of sector j in the studied area i at period 0 (i.e., the beginning of the period), $E^{(t)}$ is the total CO_2 emissions of all sectors in the reference area at period t. The positive (negative) value of NS_{ij} represents the large (small) contributions of sector j to CO_2 emissions and sector j is the growth-oriented (declining) sector in terms of CO_2 emissions changes.

$$IS_{ij} = \sum_{t=1}^{k} e_{ij}^{(0)} \times \left[\frac{E_j^{(t)} - E_j^{(t-1)}}{E_j^{(0)}} - \frac{E^{(t)} - E^{(t-1)}}{E^{(0)}} \right] \qquad (5-55)$$

where $E_j^{(t)}$ is the CO_2 emissions of sector j in the reference area at period t. The positive (negative) value of IS_{ij} represents that the growth rate of sector j in the reference area is larger (smaller) than the overall growth rate of all sectors in reference area, and the scale advantage of sector j is prominent (trivial) in CO_2 emissions because of the large (small) contribution of industrial structure to CO_2 emissions.

$$CS_{ij} = \sum_{t=1}^{k} e_{ij}^{(0)'} \times \left[\frac{e_{ij}^{(t)} - e_{ij}^{(t-1)}}{e_{ij}^{(0)}} - \frac{E_j^{(t)} - E_j^{(t-1)}}{E_j^{(0)}} \right] \qquad (5-56)$$

where $e_{ij}^{(0)'} = e_i^{(0)} \times \frac{E_j^{(0)}}{E^{(0)}}$, $e_{ij}^{(0)'}$ denotes what the CO_2 emissions of sector j in the studied area i would be if the structure of CO_2 emissions in the studied area i were equal to the reference area structure. The positive (negative) value of CS_{ij} represents that sector j in the studied area i has the competitive advantage (disadvantage) when compared to the same sector in the reference area and makes large (small) contribution to the increases of CO_2 emissions.

$$AS_{ij} = \sum_{t=1}^{k} \left(e_{ij}^{(0)} - e_{ij}^{(0)'} \right) \times \left[\frac{e_{ij}^{(t)} - e_{ij}^{(t-1)}}{e_{ij}^{(0)}} - \frac{E_j^{(t)} - E_j^{(t-1)}}{E_j^{(0)}} \right] \qquad (5-57)$$

where four possibilities of specification and competitive advantage could be provided using this formula. The positive value of AS_{ij} represents that the studied area i is specializing in increasing CO_2 emissions in sector j in which it has competitive advantage or the area i is not specializing in CO_2 emissions growth in sector j in which it has competitive disadvantage. Then the negative value of AS_{ij} is the opposite.

5.3.5. Data and policy-related parameters

Three datasets are used in this study: time-series input-output tables (IOTs), CO_2-related data, and policy-related parameters. CO_2 emissions are calculated based on energy consumption, cement production and emission factor data. Energy consumption and cement production data are from China's National Bureau of Statistics, and emissions factor data are according to (Shan et al., 2018). The policy-related parameters, including carbon intensity reduction rate, energy intensity reduction rate, energy consumption cap, the share of non-fossil fuels in the total energy consumption, are introduced in Section 5.3.2.3. The forecasts concerning IOTs, CO_2 emissions, and energy consumption are on the basis of the aforementioned datasets from 1997 to 2020 and energy consumption cap targets. The period of the forecasts is from 2021 to 2030.

5.4. Results and discussion

5.4.1. The validation of forecasted IOTs and MOOM forecasts

The uncertainty level of forecasted IOTs remains stable and level from 2021 to 2030. In detail, at the aggregate level, the Z-scores of the upper bounds of the uncertainty are around 1.962 and the Z-scores of the lower bounds of the uncertainty are about -1.968 during 2021-2030. At the sector level, Z-scores are distributed stably, and exhibit positively skewed distributions as the median values are less than the mean values. Meanwhile, some sectors and sector transactions exert larger impacts on the distribution (Figure 5-1a). For instance, the sector contributing most to the uncertainty is sector 27 (*Construction*) for most years from 2021 to 2030. The sector transaction generating most influence is from sector 12 (*Manufacture of Chemicals and Chemical Products*) to sector 12. Similarly, the uncertainty level of MOOM forecasts remains steady and level during 2021-2030. To illustrate, at the aggregate level, the Z-scores of the upper bounds of the uncertainty are about 1.966 and the Z-scores of the lower bounds are about -1.983 between 2021 and 2030. At the sector level, the distribution of Z-scores is steady, and the Z-scores present positively skewed distributions (Figure 5-1b). In the meantime, some sectors and some sector transactions have larger influences on the distribution. For example, the sector contributing most to the uncertainty is sector 29 (*Other Services*) from 2021 to 2030. The sector transaction with most influence is from sector 29 to sector 29.

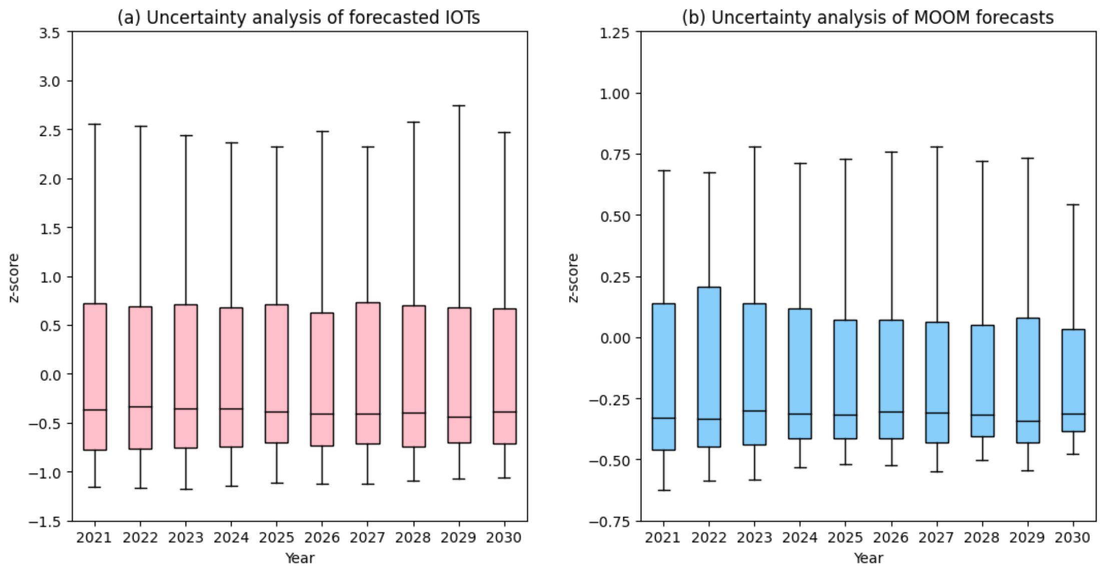

Figure 5-1 Uncertainty analyses of forecasted IOTs and MOOM forecasts

5.4.2. The feasibility of CO_2 emissions reduction in different future scenarios

According to Figure 5-2, BAU scenario and policy-related scenarios are the contexts where peak CO_2 emissions will not be fulfilled (Figures 5-2a and 5-2b). In contrast, problem-specific scenarios are the contexts where peak CO_2 emission will be achieved (Figure 5-2c). These comparisons indicate additional countermeasures could be taken to achieve CO_2 emissions peak before 2030, which is consistent with (Liu et al., 2015; Elzen et al., 2016; Liu et al., 2017; Song et al., 2018; Lu et al., 2023).

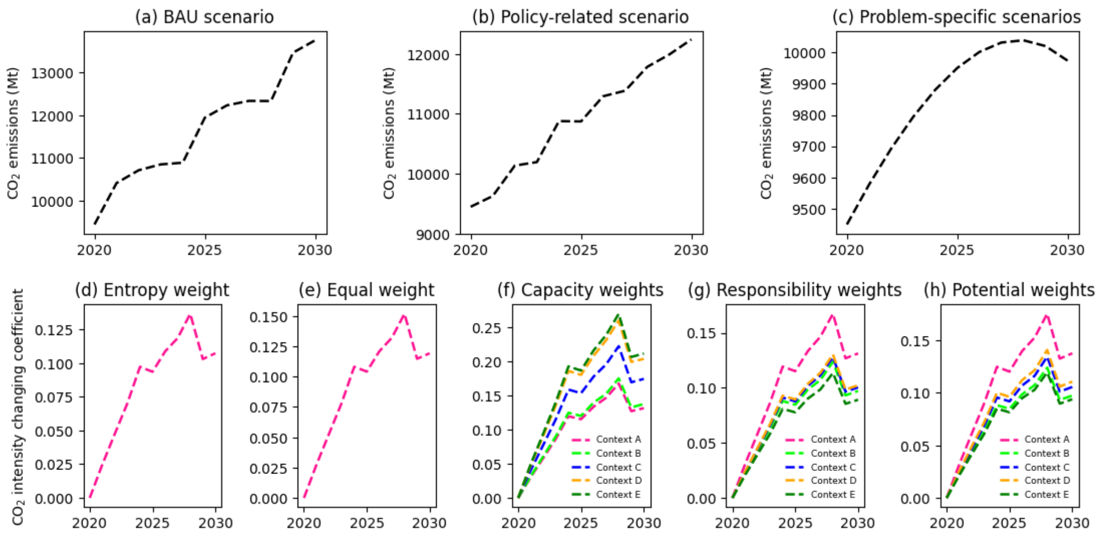

Figure 5-2 CO_2 emissions trends and CO_2 intensity changing coefficients in different future scenarios

But at the same time, it is noted that although the goal of peak CO_2 emissions will be achieved in problem-specific scenarios, the feasibilities of CO_2 emissions reduction in these scenarios are different (Figures 5-2d to 5-2h). For example, context E under capacity weights has the highest value of CO_2 intensity changing coefficient (Figure 5-2f), which indicates the lowest feasibility of CO_2 emissions reduction. For another example, context E under responsibility weights has the lowest value of CO_2 intensity changing coefficient (Figure 5-2h), which indicates the highest feasibility of CO_2 emissions reduction. Also, these results support the importance of the permutation and combination of decision preferences in specifying multi-attribute weights, which could be a complement for researches in terms of CO_2 emissions alleviation (Yi et al., 2011; Zhao et al., 2017; S.-W. Yu et al., 2018b) when traversing all the potential decision preferences among multiple attributes is needed and feasible.

Besides, peak CO_2 emissions before 2030 in these contexts from the perspective of capability weights will be fulfilled harder than those from the perspective of responsibility or potential weights (Figures 5-2f, 5-2g and 5-2h). These results indicate that if the aggregate CO_2 emission intensity reduction is allocated to sectors under the cases of preferring capacity, the sectors contributing most to total CO_2 emissions could not be considered as most important entities participating, which could hinder the process of peak CO_2 emissions before 2030. Despite these results, the capacity criterion could facilitate the decisions of investing in an environment improvement such as adding desulphurization and decarburization appliances or introducing carbon capture and storage (CCS) technology to reduce CO_2 emission intensity (Yi et al., 2011), which is another avenue of achieving CO_2 emissions alleviation (Zhao et al., 2017).

5.4.3. The structures of CO_2 emissions in different future scenarios

Different future scenarios are selected from Figure 5-2, which include BAU scenario, policy-related scenario, and the scenarios based on entropy weighting, equal weighting, context A of capacity weighting, context B of responsibility weighting and context C of potential weighting (Figure 5-3). These scenarios are also used in Sections 5.4.4 and 5.4.5. Among these selected scenarios, it is found that the structures of CO_2 emissions in 2030 do not experience large changes and maintain the similar pattern to the 2020 level. To illustrate, in the scenarios selected, in the year 2020, sector 13 (*Manufacture of Nonmetallic Mineral Products*), sector 14 (*Manufacture and Processing of Metals*), sector 23 (*Production and Supply of Electricity and Steam*), and sector 27 (*Transport, Storage and Post*) generated the largest amount of CO_2 emissions. Meanwhile, sector 8 (*Manufacture of Textile Wearing Apparel, Footwear, Leather, Fur, Feather, and Its Products*), sector 21 (*Manufacture of Measuring Instruments*), and sector 25 (*Production and distribution of water*) are the sectors with the smallest amount of CO_2 emissions. These phenomena are found to remain the same in the year 2030.

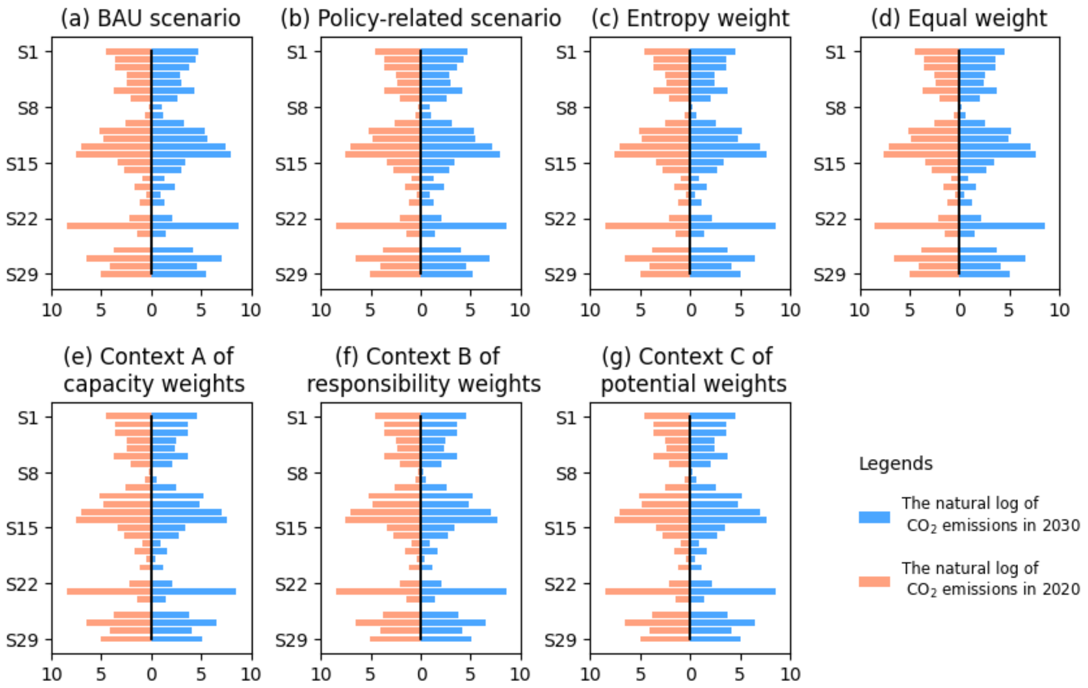

Figure 5-3 The structures of CO_2 emissions in different future scenarios

The results of the scenarios from Figures 5-3c to 5-3g indicate that although the structures of CO_2 emissions in 2030 are not changed, the realization of peak CO_2 emissions before 2030 could be achieved when CO_2 emissions are allocated across sectors on the basis of multi-criteria decision making techniques (Yi et al., 2011; Zhao et al., 2017). Then, with the specific distribution scheme of CO_2 emissions among sectors, the related CO_2 emissions alleviation measures could be taken through a scale effect, a technology effect and a structure effect (Ouyang and Lin, 2015; S. Yu et al., 2018; Chen et al., 2020; X.-Y. Zhang et al., 2020). For instance, reducing energy intensity to alleviate CO_2 emissions through the total energy consumption control, energy-saving technologies and phase-output of low efficient production activity is advocated. Also, increasing the output of low-carbon intensive sectors when controlling the expansion of the industries committing extensive energy consumption and CO_2 emission, and increasing the proportion of non-fossil fuels are supportive in CO_2 emissions reduction. Besides, the establishment and completion of carbon emission trading systems particularly for the high-carbon-emission sectors, and inter- and intra-sector collaborations for reducing CO_2 emissions are advocated (Han et al., 2017; Qin et al., 2017; Chen et al., 2020).

5.4.4. The changes of CO_2 emissions at sector level in different future scenarios

Although the structures of CO_2 emissions, as mentioned in Section 5.4.3, are unchanged, the absolute changes of sectoral CO_2 emissions matter for peak CO_2 emissions at the aggregate level (Figure 5-4). That is, to achieve the peaking of CO_2 emissions, the economy-wide efforts of sectors are needed. In detail, most sectors (26 or 25 out of 29 sectors) will account for the increment of more than 1Mt CO_2 emissions in BAU or policy-related scenario, while a majority (24 out of 29 sectors) of the sectors are expected to generate the increment of less than 1Mt CO_2 emissions in other scenarios selected (Figures 5-4a to 5-4g). At the same time, for the sectors which will have the increment of more than 1MtCO_2 emissions in BAU or policy-related scenario, these economic activities in other scenarios selected are expected to maintain or not to surpass the CO_2 emissions level of 2020 in the year 2030, so as to fulfil the goal of carbon emission peaking (Figures 5-4c to 5-4g).

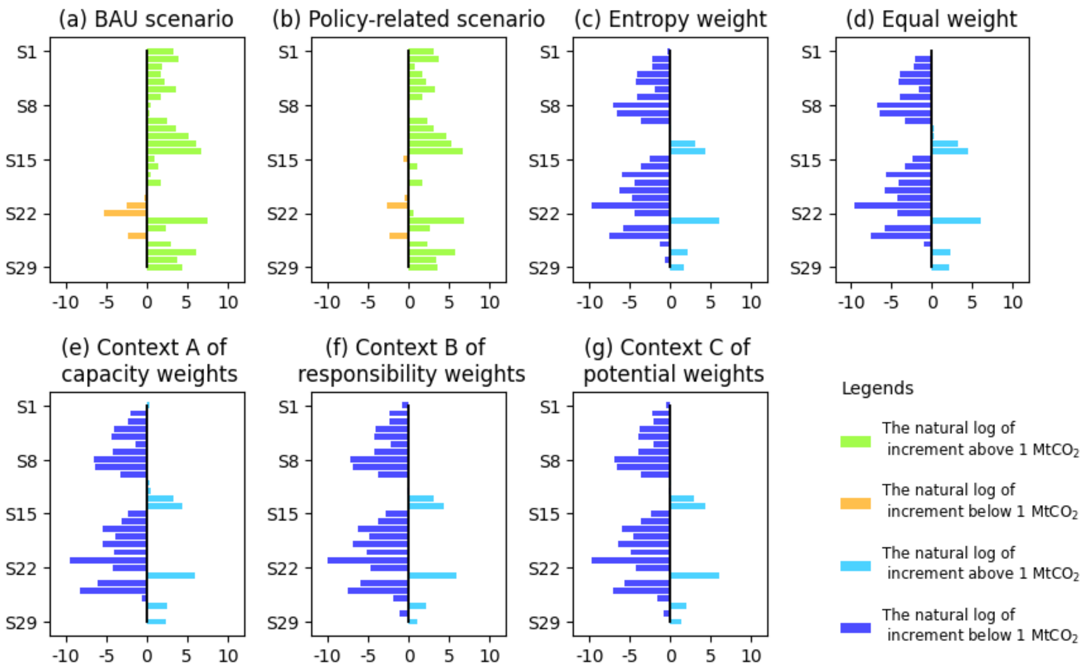

Figure 5-4 The changes of CO_2 emissions at sector level in different future scenarios

When it comes to the sectoral performance, in the BAU and policy-related scenarios, some sectors, such as sectors 23 (*Production and Supply of Electricity and Steam*) and 14 (*Manufacture and Processing of Metals*), are main sectors generating the largest incremental changes in CO_2 emissions (Figures 5-4a and 5-4b). Similarly, in other scenarios selected, these sectors are commonly regarded as the primary sectors generating the increments in CO_2 emissions (Figures 5-4c to 5-4g), which also include sectors 27 (*Transport, Storage and Post*), 13 (*Manufacture of Nonmetallic Mineral Products*), and 12 (*Manufacture of Chemicals and Chemical Products*). Despite the similarity, the CO_2 emissions of these sectors in other scenarios selected will be less than those under the BAU or policy-related scenario. But at the same time, for some sectors, such as sector 15 (*Manufacture of Fabricated Metal Products*), the BAU or policy-related scenario is expected to experience more CO_2 emissions increments than other scenarios selected, and these sectors also include sectors 22 (*Other Manufacture*), and 24 (*Production and Distribution of Gas*).

These results indicate that the redistribution of CO_2 emission across sectors, based on multi-attribute decision making techniques, is of importance and necessity to alleviate CO_2 emissions (Yi et al., 2011; Zhao et al., 2017). The reallocation of CO_2 emissions aims to ensure CO_2 emissions reduction from a holistic perspective. During the redistribution process, the sectors contributing most to total CO_2 emission reduction could be figured out through the comparisons of BAU (or policy-related) scenario with other scenarios (D. Wang et al., 2019). In this regard, the related countermeasures for sectors could be targeted and operable (D. Wang et al., 2019). Meanwhile, as for the sectors which have more increases in CO_2 emissions under other scenarios selected (Figures 5-4c to 5-4g), when carbon emissions trading systems particularly for carbon-intensive sectors are considered (Chen et al., 2020), the inter- and intra-sector collaboration in allocating the carbon quota could be supportive in CO_2 emissions reduction (Han et al., 2017; Qin et al., 2017).

5.4.5. The peak year of CO_2 emissions at sector level in different future scenarios

According to Figure 5-5, there are five sectors expected to continue increasing CO_2 emissions from 2020 to 2030 in the BAU scenario. Further, most of these sectors are energy-intensive, including sectors 3 (*Extraction of Crude Petroleum and Natural Gas*), 5 (*Mining and Quarrying of Nonmetallic Mineral and Other Mineral*), 14 (*Manufacture and Processing of Metals*), and 23 (*Production and Supply of Electricity and Steam*). The corresponding similarity and difference between the BAU scenario and policy-related scenario are exhibited (Figures 5-5b). That is, sectors 3 and 23 are expected to achieve the earlier CO_2 peak while the remaining sectors will maintain the status quo of the year 2020. When compared with the policy-related scenario, other selected scenarios show that these energy-intensive sectors are expected to reach the earlier CO_2 peak (Figures 5-5c to 5-5g). In the sense, effectuating peak CO_2 emissions at the aggregate level need to be especially based on the efforts of these industrial sectors (He, 2014; Chen et al., 2020; Fang et al., 2022), and supports the implications of Sections 5.4.3 and 5.4.4 from the perspective of timetables (Huo et al., 2023).

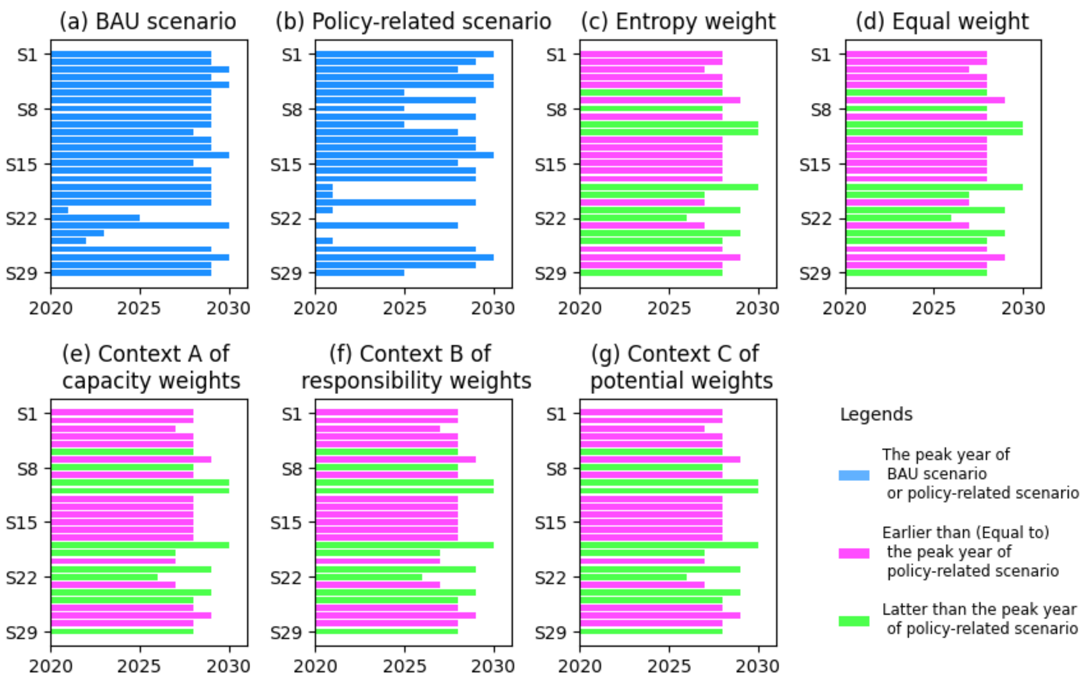

Figure 5-5 The year of peak CO_2 emissions at sector level in different future scenarios

Compared with the BAU and policy-related scenarios, other selected scenarios provide five schemes concerning CO_2 emissions allocation across sectors (Figures 5-5c to 5-5g), and show that through the reallocation of CO_2 emissions among sectors, the process of peak CO_2 emissions for some sectors (e.g., sector 21) is expected to be postponed, but peak CO_2 emissions for other sectors (e.g., sector 23) are expected to occur in advance. As a result, the aggregate CO_2 emissions reduction could be achieved in a holistic manner. For instance, in the context C of potential weights (Figure 5-5g), peak CO_2 emissions of sector 23 (*Production and Supply of Electricity and Steam*) occur in the year 2027, which is earlier than their performances in BAU and policy-related scenarios (Figures 5-5a and 5-5b). But at the same time, in the same context, CO_2 emissions of sector 21 (*Manufacture of Measuring Instruments*) will continue increasing from 2020 to 2030, which is latter than their performances in the BAU and policy-related scenarios (Figures 5-5a and 5-5b).

These results indicate that there are various potential methods to reduce CO_2 emissions at sector level. For instance, to mitigate the CO_2 emissions of sectors (e.g., sectors 14 and 23), the efforts within themselves are of significance from both production- as well as consumption-based perspectives (Zhao et al., 2017; S. Yu et al., 2018). Then, the efforts in terms of carbon emissions trading systems particularly for carbon-intensive sectors are also important (Chen et al., 2020); meanwhile, the intra- and inter-sector collaboration in allocating the carbon quota is supportive in CO_2 emissions reduction (Han et al., 2017; Qin et al., 2017). Also, the postponed time schedule concerning peak CO_2 emissions for some sectors (e.g., sector 21) could be considered as a motivation to further promote the low-carbon transition of these sectors (Chang and Chang, 2016; Han et al., 2017). Thus, the timetable derived from each context selected could not only earmark the adjustments in sectoral policies of CO_2 emissions reduction (Ouyang and Lin, 2015; Chen et al., 2020), but could also provide a reference in formulating the measures of alleviating sectoral CO_2 emissions (Huo et al., 2023).

5.4.6. The overall and dynamic changes in CO_2 emissions using SSA

The CO_2 intensity changing coefficient is the lowest in the context E of responsibility weighting, which indicates that the feasibility of CO_2 emissions reduction in this context is the highest. In this regard, context E of responsibility weighting is selected to explore the overall and dynamic changes in CO_2 emissions using SSA.

The overall changes in sector-level CO_2 emissions vary between 2020 and 2030, depending on the effect studied. To illustrate, for the area-wide effect, although all sectors will account for positive changes in CO_2 emissions, some sectors tend to have the obvious positive changes, including sector 13 (*Manufacture of Nonmetallic Mineral Products*), sector 14 (*Manufacture and Processing of Metals*), sector 23 (*Production and Supply of Electricity and Steam*) and sector 27 (*Transport, Storage and Post*) (Figure 5-6a). This result indicates that these sectors are the primary focus of CO_2 emissions increases. For the industry-mix effect, most sectors will have no apparent CO_2 emissions changes (Figure 5-6b). But in the meantime, some sectors (e.g., sector 23) are expected to exhibit the highest CO_2 growth, and some sectors (e.g., sector 27) are expected to be the largest contributors to CO_2 emissions declines (Figure 5-6b). This finding indicates that the former group of sectors could have the scale advantage in terms of CO_2 emissions increases while the latter group could perform well in CO_2 emissions reduction. For the competitive effect, most sectors are forecasted to propel the alleviation of CO_2 emissions (Figure 5-6c). But it is also noted that sectors 23 and 27 are forecasted to increase CO_2 emissions (Figure 5-6c). This comparison indicates that all sectors except sectors 23 and 27 could have the competitive advantages in curbing CO_2 emissions. For the allocation effect, most sectors will contribute to increasing CO_2 emissions and sector 23 will have the largest contribution; on the other hand, sectors 13 and 14 could decrease CO_2 emissions (Figure 5-6d). That means that for all sectors except sectors 13 and 14, they could be either specializing in increasing CO_2 emissions with a competitive advantage or not specializing in CO_2 emissions growth with a competitive disadvantage. Correspondingly, sectors 13 and 14 could experience the opposite when their allocation effects are taken into consideration. Therefore, these results derived from the influences of four categories of effects on CO_2 emissions could provide the directions and channels for CO_2 emissions synergistic reduction at sector level (Wood, 2009; Lim et al., 2009). Measures could be taken to promote CO_2 abatement synergies across sectors, including market-based policy instruments (e.g., green taxes, subsidies, and trade limits), and industrial symbiosis (Yu et al., 2015). These measures could stimulate sectoral efforts in reducing CO_2 emissions through improving the development of collective research and symbolistic technologies.

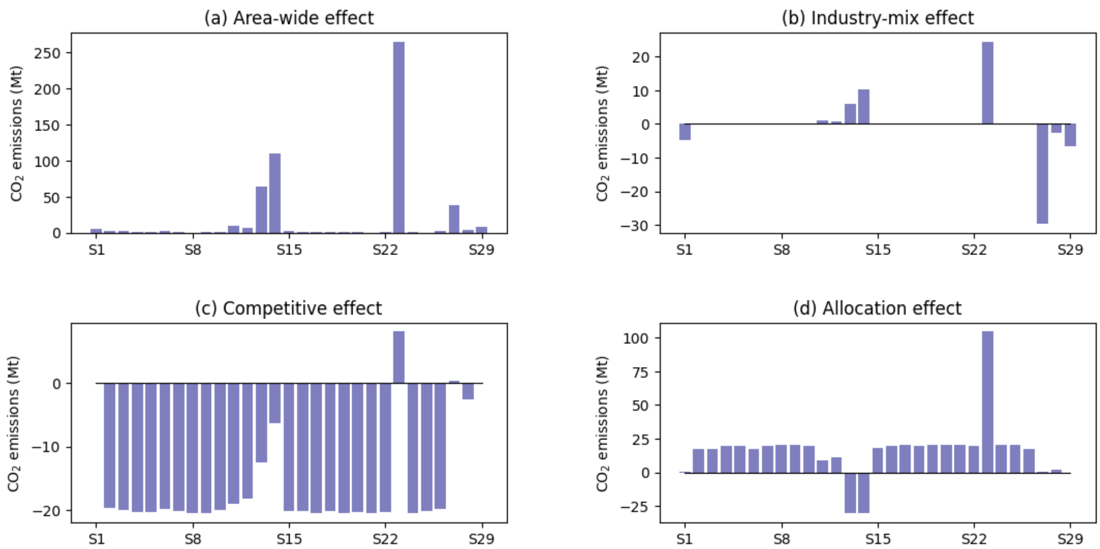

Figure 5-6 The overall changes in CO_2 emissions between 2020 and 2030

The dynamic changes in CO_2 emissions between 2020 and 2030 demonstrate the pathways of sectors for CO_2 emissions abatement. For the area-wide effect, sectors will increase CO_2 emissions in the early years but are expected to decrease CO_2 emissions after several years (Figure 5-7a). For the industry-mix effect, some sectors (e.g., sector 23) will go through CO_2 emissions growth for a longer period of time while some sectors (e.g., sector 27) will experience CO_2 emission declines from the beginning (Figure 5-7b). For the competitive effect, when most sectors will be reducing CO_2 emissions, sectors 14 and 23 are forecasted to undergo fluctuations in the amount of

CO_2 emissions (Figure 5-7c). Also, sector 14 will increase CO_2 emissions for the latter years but sector 23 will experience the opposite (Figure 5-7c). For the allocation effect, most sectors will generate the increases in CO_2 emissions; sectors 14 and 23 could have the fluctuations in the amount of CO_2 emissions (Figure 5-7d). The difference is there will be CO_2 emissions frequent increases in sector 14, while sector 23 is prone to have more CO_2 emissions declines. These results not only inform the annual future trends which sector-level CO_2 emissions are expected to experience, but they also provide a reference when the synergistic deployment of CO_2 emissions alleviation among sectors is implemented (Chen et al., 2020; Wu et al., 2023), and the sequential peaking of CO_2 emissions in different sectors is promoted (Niu et al., 2016; N. Zhou et al., 2018).

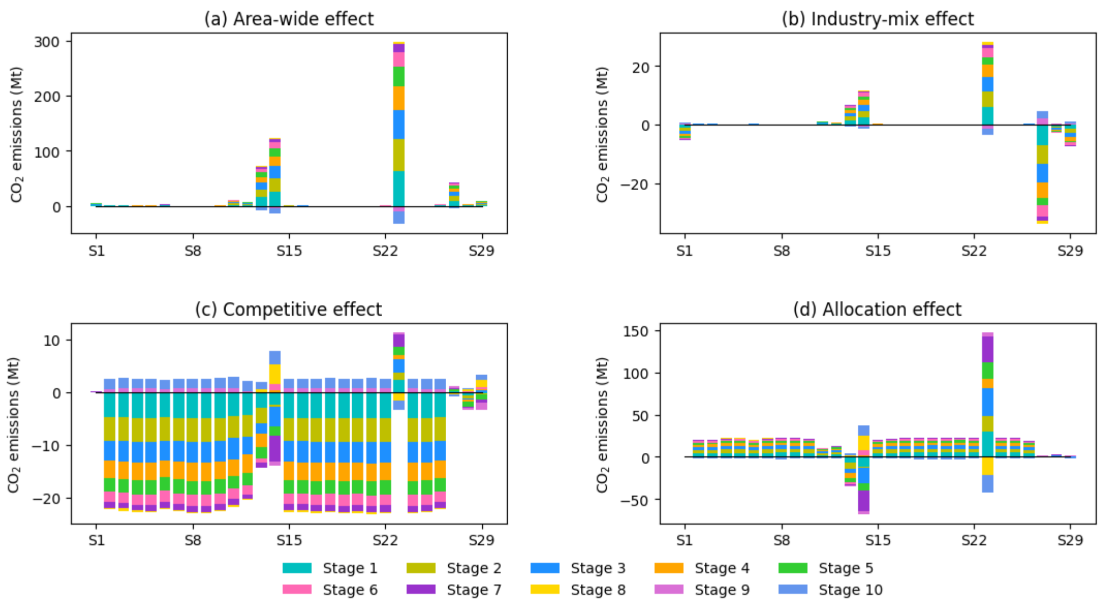

Figure 5-7 The dynamic changes in CO_2 emissions between 2020 and 2030

5.5. Conclusion

Input-output analysis (IOA) in a scenario context could not only encompass the intra- and inter-sector linkages in future scenarios, but also explore the potential pathways of external variables. During the integration of IOA and scenario analysis, multi-criteria decision making (MCDM) has been found to be feasible and useful. Against this backdrop, we propose an integrated scheme of input-output future scenarios construction to help alleviate CO_2 emissions in a holistic manner. That is, we set up three categories of input-output future scenarios by interconnecting production and consumption. We start the input-output BAU scenario through a procedure of input-output forecasting on the basis of MMTT. We then construct the input-output policy-related scenario by extending the multi-objective optimization method with multiple policy-related parameters. We finally arrange the input-output problem-specific scenarios using multi-attribute decision making which incorporates the generalized weighting method with the permutation and combination method, and supports the construction of a multi-attribute importance method. Within the three constructed categories of input-output future scenarios, sector-level CO_2 emissions alleviation is analysed. This study is in the case of China from 2020 to 2030. The main results and implications are as follows.

The validation results show that the uncertainty level of forecasted IOTs remains stable and level from 2021 to 2030, with the Z-scores of the upper bounds of the uncertainty being around 1.962 and the Z-scores of the lower bounds of the uncertainty being about -1.968 from 2021 to 2030. Similarly, the uncertainty level of MOOM forecasts remains steady and level during 2021-2030, with the Z-scores of the upper bounds of the uncertainty being about 1.966 and the Z-scores of the lower bounds being about -1.983 from 2021 to 2030. Besides, the sectors and sector transactions contributing most to the uncertainties of forecasted IOTs and MOOM forecasts are figured out respectively.

Regarding CO_2 emissions synergistic alleviation within input-output future scenarios, there are several main results. First, the scenarios where peak CO_2 emissions are achieved are identified, which indicates that additional measures for CO_2 emissions reduction are needed. Second, among the identified contexts, the structures of CO_2 emissions in 2030 do not experience large changes and maintain the similar pattern to the 2020 level, which emphasizes that CO_2 emissions reduction is expected to continue focusing on the efforts of specific sectors. Third, for the economy-wide effects of CO_2 emissions alleviation, the changes of CO_2 emissions suggest the importance of reallocating CO_2 changes among sectors in a holistic manner. Fourth, the timetable derived from each scenario selected could not only earmark the adjustments in the sectoral policies of CO_2 emissions reduction, but also could provide a reference for formulating the measures of alleviating CO_2 emissions at sector level. Finally, the overall and dynamic changes in CO_2 emissions using SSA inform the directions and channels for CO_2 emissions reduction at sector level, and provide a reference when the synergistic deployment of CO_2 emissions alleviation among sectors is implemented and the sequential peaking of CO_2 emissions among sectors is promoted.

Chapter 6: Input-output future configuring system for low-carbon economy using a social accounting matrix optimization design

6.1. Introduction

Input-output optimization for forecasting has attracted increasing interest in low-carbon economy (LCE) study (Y.-Q. Su et al., 2021). To illustrate, the low-carbon scenarios are developed to define and establish the feasible countermeasures (Nguyen et al., 2018). The low-carbon measures under multiple constraints are evaluated for determining the optimum situations (Kang et al., 2020). The socio-economic impacts for CO_2 emissions peak are assessed for investigating the pathways in which CO_2 emissions peak could be achieved (Mi et al., 2017c; S.-W. Yu et al., 2018a). The effects of CO_2 emissions on resources are optimized for addressing the changes from climate change (Aviso et al., 2018). The influences of CO_2 abatement measures are gauged through achieving general equilibrium (Dong et al., 2017).

However, there are still some attempts to make for input-output forecasting studies in the context of LCE. First, despite the significance of composite indicators has been recognized (Wang et al., 2010; H.-S. Lin et al., 2020), the optimization of composite indicators has not been undertaken in input-output forecasting studies. Second, although the role of energy intensity and CO_2 intensity in CO_2 emission reduction has drawn the attention (Xiao et al., 2017; Li et al., 2019), the relation among energy intensity, CO_2 intensity, total energy consumption, and the growth rate of GDP has not been investigated for the optimum situations. Third, because computable general equilibrium (CGE) model focuses on general equilibrium, rather than a pursuit of optimization (Sharify and Batey, 2006), the social accounting matrix (SAM) optimization model could improve this point by integrating CGE with optimization.

These aforementioned attempts constitute the key features of a new input-output forecasting method, which is what we have termed input-output future configuring system in this study, corresponding to the connotation of configuration in the organizational theory (Rosenberg, 1968; Miller and Friesen, 1978). This system could fulfil the following aspects. First, the effects in terms of volume and structure could be reflected to help with the countermeasures design (Li et al., 2019; Y.-Q. Su et al., 2021). Second, the future trends at sector level in the context of LCE could be delineated to facilitate the preparation for future changes (San Cristóbal, 2010; Igos et al., 2015). Third, this system could attain adjustments and achieve flexibilities when the influencing variables are changed (Singh and Panda, 1989).

Therefore, in this study, to reflect and reconcile the future trends in the context of LCE, we propose an input-output future configuring system. This system is constructed by a SAM optimization design, which is achieved within the CGE-based framework. During the system construction, optimum designs are conducted for LCE performance and planning-based parameter setting. Then, a CGE appraisal framework is integrated into optimization. Also, this system is validated through Monte Carlo simulations. When applying this system to the context of LCE, a new method is proposed through combining the element-based Fourier method (EFM) with the simultaneous equations method (SEM), so as to analyse the impacts of future trends on economy, energy and CO_2 emissions and suggest countermeasures correspondingly. This study is in the case of China from 2020 to 2030. The remainder of this paper is organized as follow. Section 6.2 introduces the research concerning the input-output future configuring system, SAM optimization design, and LCE performance with optimization. Section 6.3 introduces the methodology and data. Section 6.4 is about results and discussion. Section 6.5 concludes this paper.

6.2. Literature review

6.2.1. Input-output future configuring system

A configuration represents a number of specific and separate attributes which are meaningful collectively rather than individually (Rosenberg, 1968; Miller and Friesen, 1978), which contains relationships among elements or items representing multiple domains (Dess et al., 1993). Elements or items from a configurational perspective are conceived as constellations of inter-connected internal and external structures, and a configurational perspective is of predictive importance (Miller, 1990; Delery and Doty, 1996). In this sense, a configurational perspective could be developed towards tracking the development of organizations when the organizations are affected by the internal and external changes over time (C. Zhang et al., 2017). Not only does a configuration perspective gain popularity in organizational theory and strategy research (Fiss, 2007), but it is also developed in other fields, such as economy (F.-F. Jiang et al., 2021), energy (Kimmich and Tomas, 2019), and environment (J.-F. Wu et al., 2021).

From a configurational perspective, the input-output future configuring system within a SAM scheme develops towards a system of multidimensionality; meanwhile the role of economic activity-level interdependencies adds up in this system. Besides, the input-output system is expected to respond the temporal changes internally and externally to reflect the system-level evolution. But at the same time, a configurational perspective per se does not emphasize the optimization of system, so there is a need for optimizing this input-output system to develop the configurational perspective (Hristu-Varsakelis et al., 2012). In these regards, the detailed, holistic, integrated image of this system is yielded (Bensaou and Venkatraman, 1995; F.-F. Jiang et al., 2021), promoting the effectiveness of this system.

Based on the previous studies, for the construction of input-output future configuring system, a configurational perspective is exploited and integrated into input-output system; meanwhile the characteristics of input-output system are retained. Also, the prospective feature of this system could be reflected and utilized for impact analysis and planning. Then, the influencing variables to consider could be processed following the formed input-output configuring procedure, so as to meet the specified adjustments (Xiao et al., 2017; Lin and Jia, 2018, 2020). Besides, during the construction of input-output future configuring system, the optimization feature of this system is achieved (Wang et al., 2010; H.-S. Lin et al., 2020), further developing the configurational perspective.

6.2.2. Social accounting matrix optimization design

Optimization models have been incorporated into input-output systems, which allows for the optimal performance of economic activities when making choices as to constraints (Ochitwa, 1984; Nguyen et al., 2018). The related studies could be clarified into two categories: one is for what if scenarios and the other is for what best scenarios (Pulido-Velazquez et al., 2008). Models for the former category are better suitable to reproduce the modus operandi of the system under the current institutional settings (Nguyen et al., 2018; Kang et al., 2020). By contrast, models for the latter category are useful to systematically search for the promising planning and management solutions (San Cristóbal, 2010; Yu et al., 2016b). The integration of mathematical programming with input-output system has been gradually extended to analyse the sector-level impacts of countermeasures (San Cristóbal, 2012), provide the applicability as a management avenue (Singh and Panda, 1989), and improve the efficiency of decision making (Hristu-Varsakelis et al., 2012). Compared to social accounting matrices, input-output tables are more widely used in this integration, although the former delineate both product and income values for an economy system comprehension (Sharify, 2021).

Computable general equilibrium (CGE) model is a useful tool for studying economic activity-level interdependence and general equilibrium repercussions in depth (Cardenete et al., 2017). The product and income flows between economic activities are of necessity for the CGE model, delineating the mutual influence and interdependence among various economic activities (Liang et al., 2022). Within in a

CGE appraisal, the economy consists of supply and demand is equalized across interconnected markets in the economy, and the abstract general equilibrium structure is combined with realistic economic data to solve numerically for the levels of supply, demand and price that support equilibrium across a specified set of markets (Cheng et al., 2015). CGE model has been widely used in diverse fields such as economy (L.-G. Zhang et al., 2018), energy (Lin and Jia, 2020), and environment (Xiao et al., 2017).

CGE model is built on the basis of social accounting matrix (SAM). Within a SAM scheme, the economic transactions are captured and the SAM optimization method is conducted for economic planning (Sharify, 2021). SAM optimization approach combines SAM with mathematical programming to attain the optimum level when considering goals and constraints, which improves CGE model encompassing the general equilibrium of economic activities. Also, because SAM reflects both product as well as income flows, the SAM optimization method has the capability of responding to these reflections for the purpose of planning.

However, there are two points which previous studies have not attached enough attention on. First, previous studies are less prone to study the importance of the predictability of the SAM optimization method (Ochitwa, 1984). Second, previous studies have not emphasized more on integrating CGE with SAM optimization, although this integration is capable of encompassing the advantages of both models (Sharify and Batey, 2006). So in this study, we construct the input-output future configuring system, which is achieved by integrating CGE with SAM optimization. In this regard, this input-output future configuring system could utilize the merits of SAM, mathematical programming and CGE for impact analysis and management.

6.2.3. Low-carbon economy performance with optimization

Low-carbon economy (LCE) is to achieve more economic outcomes, higher living quality, less depletion of natural resources, and less environmental contamination (UK

Department Trade, 2003; Peng and Deng, 2021). Quantifying the LCE performance is of significance as this quantification could not only help comprehend the development of LCE, but also help the management for LCE. In detail, the LCE system has been constructed considering economy, society, energy and environment subsystems, so as to provide a systematic framework for CO_2 reduction and low-carbon transition (Shi et al., 2022). Also, the composite index for LCE has perceived as useful for evaluating low-carbon development (Tan et al., 2017).

However, current quantifying LCE performance has not concentrated more on the optimization of LCE performance, which decreases the applicability of these useful methods to improve LCE performance. When it comes to how to achieve the optimization of LCE performance, not only does this corresponding method highlight the role of economy, society, energy, and environment (Tan et al., 2017; Shi et al., 2022), but it also encompasses the optimization of the composite index to establish. The latter, in particular, has been achieved in the field of energy (Wang et al., 2010; H.-S. Lin et al., 2020). Then, regarding the composite index to establish for LCE performance, previous studies have pointed out the usefulness of the indicators such as economic value per unit of CO_2 emissions (Heil and Wodon, 1997), energy consumption per unit of CO_2 emissions (Feng et al., 2015), and disposable income (for social welfare) per unit of CO_2 emissions (Ürge-Vorsatz et al., 2016; Zhou et al., 2017). These indicators depict the relationships about the role of economy, energy and society in CO_2 emissions. The higher value of these indicators indicate the better LCE performance.

Also, it is noted that there is a need for quantifying role of planning-based parameters in improving LCE performance. In the context of LCE in China, the planning-based parameters include the planning in terms of economy, energy, and CO_2 emissions. Because there are relations among economy, energy and CO_2 emissions, the optimum situation delineating the synergic effects of these contributing factors could be gained for better LCE performance.

Therefore, in this study, we propose an input-output future configuring system for LCE, which is constructed by a SAM optimization design. During the system construction, the composite index for LCE performance is compiled to serve as the objective of this optimization design, the optimum situation concerning the trade-off among objectives in terms of economy, energy and CO_2 emissions is calculated for one of constraints of this optimization design, and the general equilibrium within a CGE appraisal is also among constraints of this optimization design. The validation of this system is conducted through Monte Carlo simulations. Besides, when applying this SAM optimization design to the context of LCE, a new method is proposed through combining the element-based Fourier-Markov method (EFM) with the simultaneous equation method (SEM), so as to analyse the effects of future trends on economy, energy and CO_2 emissions at the aggregate and sector levels and to gain specified and operable low-carbon countermeasures.

6.3. Method and data

6.3.1. Optimum designs for LCE performance and planning-based parameter setting

The LCE performance composite indicator could be explained as follows.

$$F = m\sum_{i}\boldsymbol{u_i} + nv + q\sum_{i}\boldsymbol{k_i} \qquad (6-1)$$

where F is the composite indicator of LCE performance, $\boldsymbol{u_i}$ is the value added per unit of CO_2 emissions for sector i, v is the energy consumption per unit of CO_2 emissions, $\boldsymbol{k_i}$ is the disposable income per unit of CO_2 emissions for sector i, m, n and q are the weights of each indicator considered in F.

The indicators are normalized, according to a larger value of a positive indicator indicating the better performance with a smaller value of a negative indicator indicating the better performance (Mi et al., 2017b; Shen et al., 2021). The normalization is expressed as follows.

$$z_{ij} = \left(n_{ij} - n_{ij}^{min}\right)/\left(n_{ij}^{max} - n_{ij}^{min}\right) \qquad (6-2)$$

$$z_{ij} = \left(n_{ij}^{max} - n_{ij}\right)/\left(n_{ij}^{max} - n_{ij}^{min}\right) \qquad (6-3)$$

where n_{ij} is the feature value of the indicator, subscript i denotes the alternative to sort in the dataset, subscript j denotes the indicator, z_{ij} is the normalized value of the indicator, $n_{ij}^{min} = \min_{i} n_{ij}$, and $n_{ij}^{max} = \max_{i} n_{ij}$.

As for the optimum design for LCE planning-based parameter setting in China, the simultaneous consideration of diverse planning-based parameters is explained as follows.

$$C_t = E_l Z_l (1 - (t - l)\beta)(1 + \gamma)^{(t-l)} \qquad (6-4)$$

where C_t is the CO_2 emissions in year t, E_l is the CO_2 intensity in year l, Z_l is the GDP in year l, β is the average reduction rate of CO_2 emission intensity, and γ is the average growth rate of GDP.

According to planning-based parameters in terms of economy and CO_2 emissions, the optimum situation for attaining the growth rate of GDP is as follows.

$$\gamma_{opt} = exp(\beta/(1 - (t - l)\beta)) - 1 \qquad (6-5)$$

where γ_{opt} is the optimum growth rate of GDP when the planning-based parameters in light of economy and CO_2 emissions are considered.

Then, when planning-based parameters in terms of energy consumption are considered, the optimum situation of attaining the growth rate of GDP is adjusted as follows.

$$\gamma'_{opt} = \sqrt[(t-l)]{E_{cap,t}/f_l Z_l(1-(t-l)\alpha)} - 1 \qquad (6-6)$$

where γ'_{opt} is the adjusted growth rate of GDP, f_l is the energy intensity in year l, and α is the average reduction rate of energy intensity.

6.3.2. Integrating CGE with SAM optimization

6.3.2.1. Production block

In the production block, each production function is the Constant Elasticity of Substitution (CES) function except for the intermediate inputs composition which is Leontief production function.

$$\boldsymbol{QA_a = \alpha_a^q \left[\delta_a^q QVA_a^{\rho_a^q} + (1-\delta_a^q) QINTA_a^{\rho_a^q}\right]^{1/\rho_a^q}} \qquad (6-7)$$

$$\boldsymbol{\frac{PVA_a}{PINTA_a} = \frac{\delta_a^q}{(1-\delta_a^q)}\left(\frac{QINTA_a}{QVA_a}\right)^{1-\rho_a^q}} \qquad (6-8)$$

$$\boldsymbol{PA_a \cdot QA_a = PVA_a \cdot QVA_a + PINTA_a \cdot QINTA_a} \qquad (6-9)$$

where $\boldsymbol{QA_a}$ are the quantities of domestic production, $\boldsymbol{QVA_a}$ are the quantities of value added, $\boldsymbol{QINTA_a}$ are the quantities of the intermediate input, $\boldsymbol{PA_a}$ is the prices of domestic production, $\boldsymbol{PVA_a}$ is the prices of value added, $\boldsymbol{PINTA_a}$ is the prices of intermediate inputs, $\boldsymbol{\alpha_a^q}$ are the efficiency parameters of CES, $\boldsymbol{\delta_a^q}$ are the share parameters of CES, $\boldsymbol{\rho_a^q}$ are the elasticity parameters of CES, and $\boldsymbol{a}$ denotes the production sector.

$$\boldsymbol{QVA_a = \alpha_a^{va}\left[\delta_a^{va}QLD_a^{\rho_a^{va}} + (1-\delta_a^{va})QKD_a^{\rho_a^{va}}\right]^{1/\rho_a^{va}}} \qquad (6-10)$$

$$\boldsymbol{\frac{WL}{WK} = \frac{\delta_a^{va}}{(1-\delta_a^{va})}\left(\frac{QKD_a}{QLD_a}\right)^{1-\rho_a^{va}}} \qquad (6-11)$$

$$\boldsymbol{PVA_a \cdot QVA_a = WL \cdot QLD_a + WK \cdot QKD_a} \qquad (6-12)$$

where $\boldsymbol{QLD_a}$ are the demand for labour, $\boldsymbol{QKD_a}$ are the demand for capital, $\boldsymbol{WL}$ are the prices of labour, $\boldsymbol{WK}$ are the prices of capital, $\boldsymbol{\alpha_a^{va}}$ are the efficiency parameters of CES, $\boldsymbol{\delta_a^{va}}$ are the share parameters of CES, $\boldsymbol{\rho_a^{va}}$ are the elasticity parameters of CES.

$$\boldsymbol{QINT_{ca} = ica_{ca} \cdot QINTA_a} \qquad (6-13)$$

$$\boldsymbol{PINTA_a = \sum\nolimits_c ica_{ca} \cdot PQ_c} \qquad (6-14)$$

where $\boldsymbol{QINT_{ca}}$ are the intermediate inputs from commodity sector $\boldsymbol{c}$ to production sector $\boldsymbol{a}$, $\boldsymbol{ica_{ca}}$ are the quantities of commodity $\boldsymbol{c}$ to produce one unit of intermediate input of $\boldsymbol{a}$, $\boldsymbol{PINTA_a}$ are the prices of intermediate inputs, and $\boldsymbol{PQ_c}$ are the prices of commodities.

6.3.2.2. Commodity block

In the commodity block, a Constant Elasticity of Transformation (CET) function is applied to allocate the total domestic production into two parts: export and domestic consumption.

$$\boldsymbol{QX_c = \alpha_c^x\left[\delta_c^x QDA_c^{\rho_c^x} + (1-\delta_c^x)QE_c^{\rho_c^x}\right]^{1/\rho_c^x}} \qquad (6-15)$$

$$\frac{\boldsymbol{PDA_c}}{\boldsymbol{PE_c}} = \frac{\boldsymbol{\delta_c^x}}{(\boldsymbol{1} - \boldsymbol{\delta_c^x})}\left(\frac{\boldsymbol{QE_c}}{\boldsymbol{QDA_c}}\right)^{\boldsymbol{1}-\boldsymbol{\rho_c^x}} \qquad (6-16)$$

$$\boldsymbol{PX_c} \cdot \boldsymbol{QX_c} = \boldsymbol{PD_c} \cdot \boldsymbol{QDA_c} + \boldsymbol{PE_c} \cdot \boldsymbol{QE_c} \qquad (6-17)$$

$$\boldsymbol{PE_c} = \boldsymbol{pwe_c} \cdot \boldsymbol{EXR} \qquad (6-18)$$

where $\boldsymbol{QX_c}$ are the outputs of commodities, $\boldsymbol{QDA_c}$ are the quantities of domestic commodities, $\boldsymbol{QE_c}$ are the quantities of exports, $\boldsymbol{PX_c}$ are the prices of commodities, $\boldsymbol{PDA_c}$ are the prices of domestic commodities, $\boldsymbol{PE_c}$ are the prices of exports, $\boldsymbol{\alpha_c^x}$ are the efficiency parameters of CET, $\boldsymbol{\delta_c^x}$ are the share parameters of CET, $\boldsymbol{\rho_c^x}$ are the elasticity parameters of CET, $\boldsymbol{pwe_c}$ are after-tax Free On Board (FOB) prices, and $\boldsymbol{EXR}$ is exchange rate.

In the commodity block, the total commodity in the domestic market is from two sources: the total commodities produced and consumed domestically, and the imported commodities. An Armington CES function is used to delineate the relationship.

$$\boldsymbol{QQ_c} = \boldsymbol{\alpha_c^q}\left[\boldsymbol{\delta_c^q}\boldsymbol{QDC_c^{\rho_c^q}} + (\boldsymbol{1} - \boldsymbol{\delta_c^q})\boldsymbol{QM_c^{\rho_c^q}}\right]^{\boldsymbol{1}/\boldsymbol{\rho_c^x}} \qquad (6-19)$$

$$\frac{\boldsymbol{PDC_c}}{\boldsymbol{PM_c}} = \frac{\boldsymbol{\delta_c^q}}{(\boldsymbol{1} - \boldsymbol{\delta_c^q})}\left(\frac{\boldsymbol{QM_c}}{\boldsymbol{QDC_c}}\right)^{\boldsymbol{1}-\boldsymbol{\rho_c^q}} \qquad (6-20)$$

$$\boldsymbol{PQ_c} \cdot \boldsymbol{QQ_c} = \boldsymbol{PDC_c} \cdot \boldsymbol{QDC_c} + \boldsymbol{PM_c} \cdot \boldsymbol{QM_c} \qquad (6-21)$$

$$\boldsymbol{PM_c} = \boldsymbol{pwm_c} \cdot (\boldsymbol{1} + \boldsymbol{tm_c}) \cdot \boldsymbol{EXR} \qquad (6-22)$$

where $\boldsymbol{QQ_c}$ are the quantities of commodities in domestic market, $\boldsymbol{QDC_c}$ are the quantities of domestic commodities, $\boldsymbol{QM_c}$ are the quantities of imports, $\boldsymbol{PQ_c}$ are the prices of commodities in domestic market, $\boldsymbol{PDC_c}$ are the prices of domestic commodities, $\boldsymbol{PM_c}$ are the prices of imports, $\boldsymbol{\alpha_c^q}$ are the efficiency parameters of Armington CES, $\boldsymbol{\delta_c^q}$ are the share parameters of Armington CES, $\boldsymbol{\rho_c^q}$ are the elasticity parameters of Armington CES, $\boldsymbol{pwm_c}$ are the international prices of commodities, and $\boldsymbol{tm_c}$ are the import tariff rates.

6.3.2.3. Household block

$$\boldsymbol{YH_p = WL \cdot QLS_p + shif_{hk} \cdot WK \cdot QKS_p + TRhg_p + TRhent_p + TRhrow_p} \quad (6-23)$$

$$\boldsymbol{PA_c \cdot QH_c^p = \left(1 - ti_p\right) \cdot shrh_c^p \cdot mpc_p \cdot YH_p} \qquad (6-24)$$

where $\boldsymbol{YH_p}$ is the income of household p, $\boldsymbol{QLS_p}$ are quantities of labour, $\boldsymbol{QKS_p}$ are quantities of capital, $\boldsymbol{shif_{hk}}$ is the transfer from capital to household**,** $\boldsymbol{TRhg_p}$ is the transfer payment from government to household, $\boldsymbol{TRhent_p}$ is the transfer payment from enterprise to household, $\boldsymbol{TRhrow_p}$ is the transfer payment from rest of world (ROW) to household, $\boldsymbol{QH_c^p}$ is the household consumption, $\boldsymbol{ti_p}$ is the rate of individual income tax, $\boldsymbol{shrh_c^p}$ is the share of commodity in total household consumption, and $\boldsymbol{mpc}$ is the marginal propensity to consume.

6.3.2.4. Enterprise block

$$\boldsymbol{YENT = WK \cdot QKS \cdot shif_{entk}} \qquad (6-25)$$

where $\boldsymbol{YENT}$ is the earning of enterprise from capital income, and $\boldsymbol{shif_{entk}}$ is the share in total domestic capital income.

$$\boldsymbol{ENTSAV = (1 - ti_{ent})YENT - TRhent_p} \qquad (6-26)$$

where $\boldsymbol{ENTSAV}$ is the saving of enterprise, and $\boldsymbol{ti_{ent}}$ is the enterprise income tax rate.

$$\boldsymbol{EINV} = \sum_c \boldsymbol{PQ_c} \cdot \boldsymbol{QINV_c} \qquad (6-27)$$

where $\boldsymbol{EINV}$ is the investment of enterprise, and $\boldsymbol{QINV_c}$ are the investment quantities of commodities.

6.3.2.5. Government block

$$\boldsymbol{YG} = \sum_a (\boldsymbol{tval_a} \cdot \boldsymbol{WL} \cdot \boldsymbol{QLD_a} + \boldsymbol{tvak_a} \cdot \boldsymbol{WK} \cdot \boldsymbol{QKD_a}) + \sum_p \boldsymbol{YH_p} \cdot \boldsymbol{ti_p} + \boldsymbol{YENT} \cdot \boldsymbol{ti_{ent}} + \sum_c \boldsymbol{tm_c} \cdot \boldsymbol{pwm_c} \cdot \boldsymbol{QM_c} \cdot \boldsymbol{EXR} + \boldsymbol{transfr_{govrow}} + \boldsymbol{YDEBT} \qquad (6-28)$$

where $\boldsymbol{YG}$ is the government revenue, $\boldsymbol{tval_a}$ denotes the rate of tax on wage in the production activity, $\boldsymbol{tvak_a}$ denotes the rate of tax on capital in the production activity, $\boldsymbol{transfr_{govrow}}$ is the transfer payment from ROW to government, and $\boldsymbol{YDEBT}$ is the debt revenue of government.

$$\boldsymbol{EG} = \sum_c \boldsymbol{PQ_c} \cdot \boldsymbol{QG_c} + \sum_p \boldsymbol{TRhg_p} + \boldsymbol{transfr_{rowgov}} \qquad (6-29)$$

where $\boldsymbol{EG}$ is the expenditure of government, $\boldsymbol{QG_c}$ denotes the government consumption of commodities, and $\boldsymbol{transfr_{rowgov}}$ is the transfer payment form government to ROW.

$$\boldsymbol{GSAV} = \boldsymbol{YG} - \boldsymbol{EG} \qquad (6-30)$$

where $\boldsymbol{GSAV}$ is the government saving.

6.3.2.6. Rest of world block

$$\boldsymbol{YROW} = \sum_c (\boldsymbol{pwm_c} \cdot \boldsymbol{QM_c} \cdot \boldsymbol{EXR}) + \boldsymbol{shif_{rowk}} \cdot \boldsymbol{WK} \cdot \boldsymbol{QKS} + \boldsymbol{transfr_{rowgov}} (6-31)$$

where $\boldsymbol{YROW}$ is the earning of ROW, and $\boldsymbol{shif_{rowk}}$ is the proportion of overseas account's domestic capital revenue in total domestic capital revenue.

$$\boldsymbol{EROW} = \sum_{c} (\boldsymbol{pwe_c} \cdot \boldsymbol{QE_c} \cdot \boldsymbol{EXR}) + \sum_{p} \boldsymbol{TRhrow_p} + \boldsymbol{transfr_{govrow}} + \boldsymbol{FSAV} \quad (6-32)$$

where $\boldsymbol{EROW}$ is the expenditure of ROW, and $\boldsymbol{FSAV}$ is the saving of ROW.

6.3.2.7. Optimization algorithm

The integration of CGE with SAM optimization goes through the following steps. First, the objective function introduced in Section 6.3.1 is the reduced form of the composite index for LCE performance. Second, the optimal design of LCE planning-based parameter is one of constraints of this integrated method. Third, the equations within a CGE appraisal, introduced in Sections 6.3.2.1-6.3.2.6, are also the constraints of this integrated method. Genetic algorithm (GA) is used for the optimization process in this study. GA has the advantages of no restrictions on derivation and function continuity (Yang et al., 2022), efficient parallelism (Campos Benvenga et al., 2016), strong global search ability (H.-S. Lin et al., 2020), straightforward implementation (Ahmadi et al., 2011), and high applicability (Roghanian and Pazhoheshfar, 2014). GA has been widely use in diverse fields, such as economy (Campos Benvenga et al., 2016), energy (Ceylan and Ozturk, 2004) and environment (Wang et al., 2010).

6.3.3. Extending input-output future configuring system with an element-based Fourier-Markov method and the simultaneous equations method

To trace the trends inherent in energy consumption and CO_2 emissions, the element-based Fourier-Markov method (EFM) combined with the simultaneous equations method is proposed. To explain the EFM method, we start with the modified Fourier correction (MFC) method with basic module. Then, we introduce the Markov process to the MFC method. Because the performance of EFM method with typical sequences has been evaluated in Chapter 4, the performance evaluation of EFM method is not included in Chapter 6. Also, we propose a new method that combines the EFM method with the simultaneous equations method (SEM) to forecast energy consumption and CO_2 emissions when the role of energy category is taken into consideration.

6.3.3.1. The MFC method with basic module

The moving average (MA) method is used as the basic module for EFM method because MA method could track both linear and nonlinear changes in time series data (Xiong et al., 2011). The MA method is explained as follows (Hansun, 2013).

$$M_t = M_{t-1} + (y_t - y_{t-n})/n \qquad (6-33)$$

where M_t is the prediction at time t, M_{t-1} is the predicted values at time $t-1$, y_t is the data point value at time t, y_{t-n} is the data point value at time $\mathrm{t}-n$, and n is the number of data points used in the calculation.

Then, the MFC approach is to increase prediction capacity from the considered input data sets. Compared with the previous use of Fourier series, this study proposes four improvements: the first one is using the quotient form of residual series to maintain the consistency between initial estimates and predictions, the second is extending the application of Fourier series to both odd and even cases (Smith, 1999; Selesnick and Schuller, 2000), the third is using the singular value decomposition (SVD) to attain the coefficients of Fourier series, and the fourth is integrating the mechanism where each element gets considered into the Fourier correction. Thus, the MFC method is explained as follows.

$$\boldsymbol{E_r} = \{E_r(1), E_r(2), \cdots, E_r(q)\}^T \qquad (6-34)$$

where E_r is the quotient form of the residuals series, and

$$E_r(k) = y_k/\hat{y}_k, k = 1, 2, \cdots, q \quad (6-35)$$

Then, the Fourier series can approximate the quotient form of residual series as follows.

$$E_r(k) = \frac{1}{2}a_0 + \sum_{i=1}^{ka}\left[a_i\, cos\left(\frac{i \cdot 2\pi}{T}k\right) + b_i\, sin\left(\frac{i \cdot 2\pi}{T}k\right)\right], k = 1, 2, \cdots, q \quad (6-36)$$

where $T = q$, and

$$k_a = \begin{cases} \frac{q}{2} + 1, if \;\; q \;\; is \;\; even \\ \frac{(q-1)}{2} + 1, if \;\; q \;\; is \;\; odd \end{cases} \quad (6-37)$$

The coefficients derived from the Fourier correction approach (i.e., $Q = [a_0, a_1, b_1, a_2, b_2, \cdots, a_{ka}, b_{ka}]^T$), are calculated as follows.

$$\boldsymbol{Q} = \boldsymbol{P}^{\dagger}\boldsymbol{E_r} \quad (6-38)$$

where $\boldsymbol{P}^{\dagger}$ is the Moore-Penrose pseudo-inverse of $\boldsymbol{P}$ as follows.

$$\boldsymbol{P} = \begin{bmatrix} \frac{1}{2} & cos\left(\frac{2\pi\cdot 2}{T}\right) & sin\left(\frac{2\pi\cdot 2}{T}\right) & cos\left(\frac{2\pi\cdot 2\cdot 2}{T}\right) & sin\left(\frac{2\pi\cdot 2\cdot 2}{T}\right) & \cdots & cos\left(\frac{k_a\cdot 2\pi\cdot 2}{T}\right) & sin\left(\frac{k_a\cdot 2\pi\cdot 2}{T}\right) \\ \frac{1}{2} & cos\left(\frac{2\pi\cdot 3}{T}\right) & sin\left(\frac{2\pi\cdot 3}{T}\right) & cos\left(\frac{2\pi\cdot 2\cdot 3}{T}\right) & sin\left(\frac{2\pi\cdot 2\cdot 3}{T}\right) & \cdots & cos\left(\frac{k_a\cdot 2\pi\cdot 3}{T}\right) & sin\left(\frac{k_a\cdot 2\pi\cdot 3}{T}\right) \\ & & & & \vdots & & & \\ \frac{1}{2} & cos\left(\frac{2\pi\cdot q}{T}\right) & sin\left(\frac{2\pi\cdot q}{T}\right) & cos\left(\frac{2\pi\cdot 2\cdot q}{T}\right) & sin\left(\frac{2\pi\cdot 2\cdot q}{T}\right) & \cdots & cos\left(\frac{k_a\cdot 2\pi\cdot q}{T}\right) & sin\left(\frac{k_a\cdot 2\pi\cdot q}{T}\right) \end{bmatrix} (6-39$$

The original prediction series can be corrected as follows.

$$\widehat{M_k} = M_k \times E_r(k), k = 1, 2, \cdots, q \quad (6-40)$$

6.3.3.2. The establishment of EFM method

The MFC method could be adjusted when there are occurred events in future (Lin et al., 2001; Hsu et al., 2009). To achieve this, the Markov process is introduced on the basis of the MFC approach. With this improvement, the new mechanism where the impact of each element on the prediction is integrated into the Fourier-Markov method, the constant good performance when compared with its original model based on is ensured, and the scope of application is complete when its current form is specified in a broad manner. This is what we have termed an element-based Fourier-Markov (EFM) method. The following is the process about how the EFM method operates.

Similar to the MFC method in Section 6.3.3.1, the EFM method uses the quotient form of residual series to maintain the consistency between initial estimates and predictions. The residual errors are portioned into r equal portions called states. Each state is an interval whose width is equal to a fixed portion of the range between the maximum and the minimum of the whole residual error (Li et al., 2007). Let S_j be the jth state.

$$S_j \in \left[SL_j, SU_j\right], j = 1, 2, \cdots, r \qquad (6-41)$$

where SL_j and SU_j are the lower and upper boundary of the jth state, and r is the integer portion of $ln(n)/\ln 2$.

$$SL_{tj} = \min_t e(t) + \frac{j-1}{r}\left(\max_t e(t) - \min_t e(t)\right) \qquad (6-42)$$

$$SU_{tj} = \min_t e(t) + \frac{j}{r}\left(\max_t e(t) - \min_t e(t)\right) \qquad (6-43)$$

where $e(t)$ is the quotient form of the residual error of the MFC method, $t = 1, 2, \cdots, q$, and $j = 1, 2, \cdots, r$.

Let $P_{ij}^{(m)}$ be the transition probability from the ith state to the jth state by m steps.

$$P_{ij}^{(m)} = \frac{R_{ij}^{(m)}}{R_i}, j = 1, 2, \cdots, r \qquad (6-44)$$

where $R_{ij}^{(m)}$ is the transition times that occurred from state i to j by m steps, and R_i is the number of data belonging to the ith state.

Let $Q_t^{(m)} = \left(P_{t1}^{(m)}, P_{t2}^{(m)}, \cdots, P_{tr}^{(m)}\right)$ be the row vector of transition probabilities of ith state at m time steps. The center vector of each state is denoted by $v = \big(v(1), v(2), \cdots, v(r)\big)$, with $v(j) = \sigma \times SL_j + (1-\sigma) \times SU_j$.

The adjusted prediction, $\widehat{M_t^{(a)}}$, in the EFM method is given by

$$\widehat{M_t^{(a)}} = \widehat{M_t} \times Q_t^{(m)} v(j) \qquad (6-45)$$

6.3.3.3. The simultaneous equations method (SEM) combined with EFM to forecast energy consumption and CO_2 emissions

When the EFM method is applied to forecast energy consumption and CO_2 emissions, the connections between energy use and CO_2 emissions and the role of energy category need to be further considered. To achieve this, we incorporate both the simultaneous equations method (SEM), as well as the policy-related parameters about energy consumption and CO_2 emissions, into the EFM method. In detail, based on the forecasting results of the EFM method, the connections between the use of each energy category and related CO_2 emissions are established by means of the SEM method, so as to ensure the changing rates of each energy category use are consistent with those of related CO_2 emissions. At the same time, the corresponding policy-related parameters including carbon intensity reduction rate, energy intensity reduction rate, the energy consumption cap target, and the shares of gas and non-fossil fuels in total energy consumption are used to ensure the configuration of the future trends in the field of energy consumption and CO_2 emissions.

6.3.4. Validation of input-output future configuring system

The validation of input-output future configuring system is achieved by Monte Carlo simulations. The uncertainty is measured by using the 2.5th and 97.5th percentiles of the data (Lu et al., 2011; Pinder et al., 2012; Lauerwald et al., 2015; Su et al., 2015; Ayarzagüena et al., 2020), which represent the upper and lower bounds respectively. To compare the variations in the uncertainty over time, a Z-score measurement (i.e., a value minus the population mean, divided by the population standard deviation) is needed. This measurement describes a value's relation to the mean of the data (i.e., a group of values) and is used to compare different datasets.

6.3.5. Data and policy-related parameters

Four datasets are used in this study: time-series social accounting matrices (SAMs), CO_2-related data, policy-related parameters, and the parameters for the CGE model integrated with SAM optimization model. CO_2 emissions are calculated based on energy consumption, cement production and emission factor data. Energy consumption and cement production data are from China's National Bureau of Statistics, and emissions factor data are according to (Shan et al., 2018). For the policy-related parameters, carbon intensity reduction rate, energy intensity reduction rate, and the share of non-fossil fuels in total energy consumption are from (NPC, 2021). Also, the energy consumption cap, and the share of natural gas in total energy consumption are from (NDRC, 2016). The parameters for the CGE model integrated with SAM optimization model include the substitution parameters between value added and intermediate inputs, the substitution parameters between labour and capital, the substitution parameters between exports and domestic products, and the substitution parameters between imports and domestic products. The benchmark SAM used in the integration of CGE model with SAM optimization model is the SAM of the year 2020. The forecasts concerning CO_2 emissions and energy consumption are on the basis of the aforementioned datasets from 1997 to 2020.

6.4. Results and discussion

6.4.1. The validation of input-output future configuring system

The uncertainty level of input-output future configuring system of China is low and stable from 2021 to 2030. At the aggregate level, the Z-scores of the lower bound of uncertainties are around -1.965 between 2021 and 2030; meanwhile, the Z-scores of the upper bound of uncertainties are around 1.952. At the economic activity level, Z-scores are distributed stably with the median lines maintaining around the Z-score of -0.314 and the interquartile range from -0.555 to 0.138, and exhibit positively skewed distributions as the median values are less than the mean values. Meanwhile, some economic activities exert larger impacts on the distribution (Figure 6-1a). For instance, the economic activity contributing most to the uncertainty is the economic activity 46 (*Urban Household account*) from 2021 to 2030. Similarly, at the economic transaction level, Z-scores are distributed stably, with the median lines sustaining around the Z-score of -0.149 and the interquartile range from -0.153 to -0.118, and exhibit positively skewed distributions. Also, some economic transactions exert larger impacts on the distribution (Figure 6-1b). For example, the economic transaction contributing most to the uncertainty is the economic transaction from economic activity 52 (*Others account*) to economic activity 50 (*Capital Factor account*).

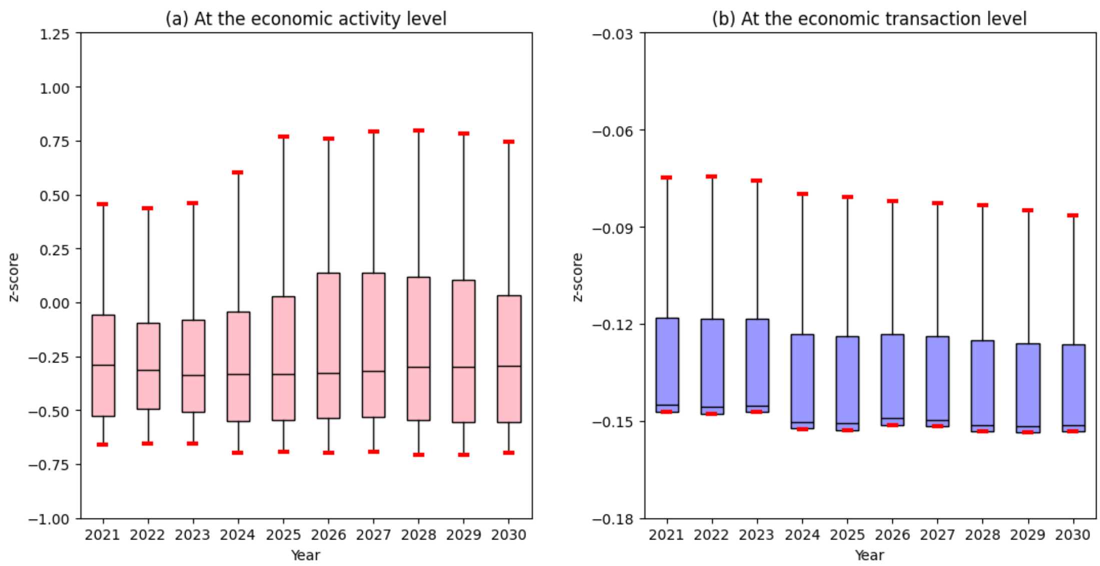

Figure 6-1 Uncertainty analyses of input-output future configuring system of China

6.4.2. The aggregate impacts based on input-output future configuring system

The aggregate impacts of input-output future configuring system of China on economy, energy consumption, and CO_2 emissions from 2020 to 2030 are illustrated in Figure 6-2. For the impacts on economy (at 1997 constant price), according to Figure 6-2a, during 2020-2030, GDP is expected to increase from 52920.68 billion yuan to 87287.94 billion yuan. Consumption is expected to continue increasing and making the largest contribution to GDP from 2020 to 2030. In detail, consumption will increase from 29033.57 billion yuan to 52331.75 billion yuan between 2020 and 2030. Investment will increase from 22571.58 billion yuan to 45820.43 billion yuan from 2020 to 2030. Export will increase from 9784.49 billion yuan in the year 2020 to 12621.70 billion yuan in the year 2030. The economic trends are hoped to continue helping in reducing the inequality of income, decreasing unfeasible fixed asset investment, and lessening China's reliance on exports (Luukkanen et al., 2015). Besides, these results indicate that to promote the economic future development, more attention could be put on the innovations in upgrading the internal structure of consumption and investment (Luukkanen et al., 2015; Yu and Du, 2019).

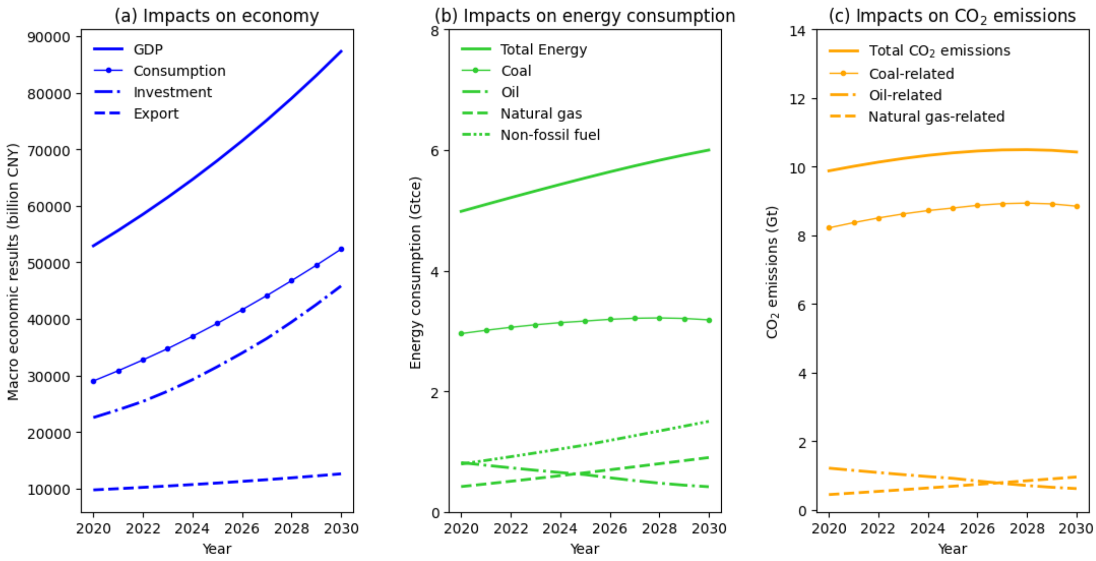

Figure 6-2 The aggregate impacts based on input-output future configuring system of China

For the impacts on energy consumption during 2020-2030, according to Figure 6-2b, the amount of total energy consumption is expected to increase from 4.98 Gton standard coal to 6.0 Gton standard coal. Despite that coal consumption will contribute most to total energy consumption during the study period, the ratio of coal use to total energy use will increase first with an annual decreasing rate of 1.06% and then will decrease from 2028 onwards. The oil consumption will experience a reduction trend with an annual decreasing rate of 6.51%. On the contrary, the consumption of natural gas and non-fossil fuel will increase from 2020 to 2030 and will contribute more to total energy use. The increasing rates are 7.96% and 6.59%, respectively. These results indicate that the structure of energy consumption could experience changes that are different from the previous structure to support the energy requirements in the future. Then, related preparations could be set up for the future necessary needs of energy consumption, including maintaining the decline in the proportion of coal consumption and preventing a rebound, and ensuring the effective supply of supply of renewable energy (S.-W. Yu et al., 2018a; Zhang and Chen, 2022).

For the impacts on CO_2 emissions during 2020-2030, according to Figure 6-2c, the total CO_2 emissions are expected to increase gradually and peak in the year 2028. The CO_2 emissions from coal use will continue contributing most to total CO_2 emissions and peak in the year 2028; the coal-related CO_2 emissions will increase first and then will start to decrease from 2028. The CO_2 emissions from oil use will decrease but the CO_2 emissions from natural gas consumption will increase. Also, the difference between the ratio of oil-related CO_2 emissions and that of gas-related CO_2 emissions will be the smallest in the year 2027. These results indicate that the changes in coal-related CO_2 emissions would continue being the core of whether total CO_2 emissions would peak or not (Xu et al., 2017). Thus, energy development and utilization technologies need be considered continuously, and in particular, strengthening independent innovation in clean coal technology and large-scale new energy technology (D. Wang et al., 2019).

6.4.3. The sector-level impacts based on input-output future configuring system

The sectoral impacts based on the input-output future configuring system are delineated in Sections 6.4.3.1-6.4.3.3. Then we analyse these sectoral impacts using the Pareto principle (also known as the 80/20 rule). The Pareto principle is a decision-making method that statistically separates a limited number of input factors (20%) have the greatest impact on an outcome (80%) (W.-W. Liu et al., 2015). This principle means if few key causes are rectified, then a better probability of success will be achieved (W.-W. Liu et al., 2015). Also, this principle allows for identifying and focusing on the key parts that contribute most to the outcomes (Robati et al., 2021).The Pareto principle has been applied in diverse fields such as economy (Zhang et al., 2022), energy (Kaur et al., 2019) and environment (Fenner et al., 2020). In what follows, critical sectors are identified in terms of the impacts on economy, energy consumption, and CO_2 emissions.

6.4.3.1. The impacts on economy

Figure 6-3 shows the sector-level impacts of input-output future configuring system on

GDP, consumption, investment and export in China from 2020 to 2030. For impacts on GDP, the scope of sectors contributing to 80% of GDP will shrink between 2020 and 2030. That is, the number of sectors constituting 80% of GDP will decrease from 9 to 7. In 2020, sector 29 (*Other Services*) will rank first in GDP, followed by sectors 28 (*Wholesale and Retail Trade*) and 1 (*Agriculture*). This tendency is expected to continue before 2026 and then the first three sectors will change to sectors 29, 28 and 26 (*Construction*). In addition, sectors 1, 27 (*Transport, Storage and Post*), 22 (*Other Manufacture*), and 14 (*Manufacture and Processing of Metals*) will also be important components contributing 80% of GDP in 2030. These results indicate that a gradual shift of the economy towards services would continue. But at the same time, the requirements for decarbonizing the identified sectors and fostering low-carbon sectors would increase (Shen and Sun, 2016; Jiang et al., 2019c).

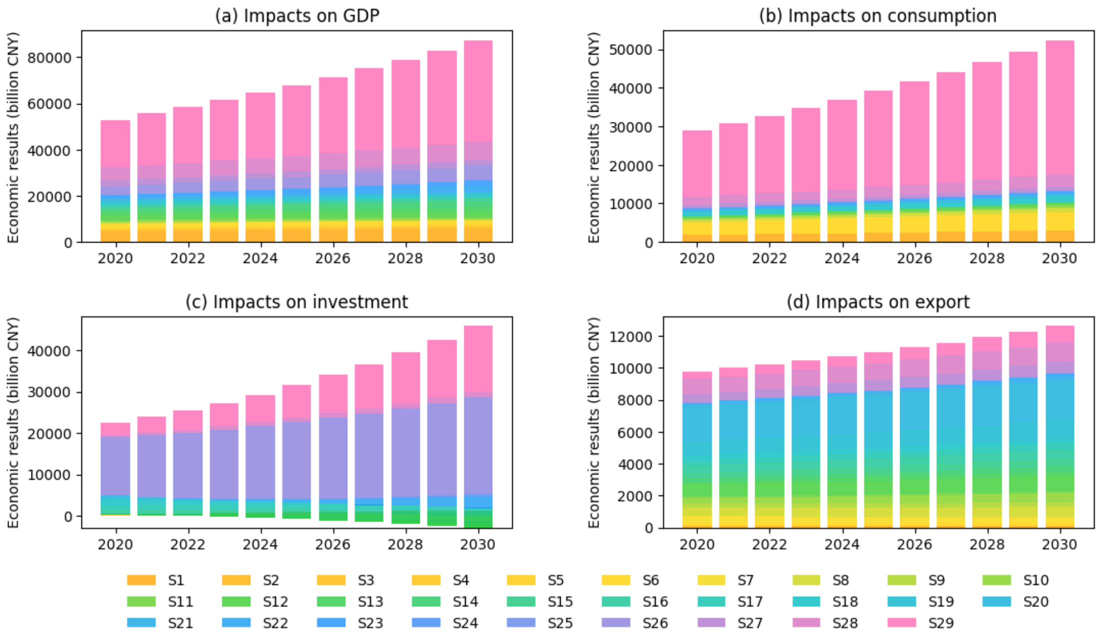

Figure 6-3 The sector-level impacts on economy based on input-output future configuring system of China

For impacts on consumption, the scope of sectors contributing 80% of consumption will shrink from 2020 to 2030. That is, the number of sectors contributing 80% of consumption would decline from 4 to 3. Also, 80% of consumption will consist of the contribution from sectors 29 (*Other Services*), 6 (*Manufacture of Food and Tobacco*), and 28 (*Wholesale and Retail Trade*) starting from the year 2020. These results indicate that on the one hand, consumption for services could be developed through the considerations of sector heterogeneity because some service sectors are carbon-intensive (Y.-Q. Su et al., 2021); on the other hand, consumption for food and tobacco could provide a close connection between production and consumption, which promotes consumption changes to affect related production changes (J. Wang et al., 2016).

For impacts on investment, the scope of sectors contributing 80% of investment will shrink during 2020-2030. That is, the number of sectors contributing 80% of investment will decline from 3 to 2. Also, 80% of investment will be composed of the contribution of sectors 26 (*Construction*) and 29 (*Other Services*) from 2020 onwards. More supports for construction industry could be provided through investing building technology research and development (B. Li et al., 2020), as well as low-carbon infrastructures (Jiang et al., 2019c). More investments in service sectors indicate an alternative to achieving a higher industrialization level. For example, promoting green finance in services sectors could be a feasible way for the upgrading of industrial structure (Wang and Wang, 2021).

For impacts on export, the scope of sectors contributing 80% of export will maintain the same level from 2020 to 2030. That is, the number of sectors contributing 80% of export will be sustained at 11. But at the same time, there will exist both sector-level homogeneity as well as sectoral heterogeneity in export. For example, the first three sectors in export in 2020 would be the same as those in 2030, and they are sectors 20 (*Manufacture of Communication Equipment, Computer and Other Electronic Equipment*), 28 (*Wholesale and Retail Trade*), and 19 (*Manufacture of Electrical Machinery and Apparatus*). But sectors contributing 80% of export in 2020 will include sector 7 (*Manufacture of Textiles*), rather than sector 17 (*Manufacture of Special-*

Purpose Machinery) which is among the sectors contributing 80% of export in 2030. These results indicate that to promote export trade, there is a need for energy structure optimization through increasing renewables and improving energy efficiency within the identified sectors (R. Huang et al., 2019). Also, the continuation of exporting the low-carbon goods and services could be taken into consideration (Mi et al., 2018a).

6.4.3.2. The impacts on energy consumption

Figure 6-4 shows the sector-level impacts on the consumption of total energy, coal, oil, and natural gas in China from 2020 to 2030, which is on the basis of input-output future configuring system. For impacts on total energy consumption, the scope of sectors consuming 80% of total energy will shrink between 2020 and 2030. That is, the number of the sectors consuming 80% of total energy will decrease from 9 to 8. Among these sectors, the first three sectors will be unchanged starting from 2022, and they include sectors 14 (*Manufacture and Processing of Metals*), 12 (*Manufacture of Chemicals and Chemical Products*), and 11 (*Manufacture of Refined Petroleum, Coke Products, Processing of Nuclear Fuel*). Then, service sectors will also be among the identified sectors. It is noted that the largest proportion of total energy consumption is accounted for by high energy-intensive sectors. Thus, there is a need for the continuation of countermeasures in terms of energy efficiency improvement, energy conservation requirements, renewable energy supports, and industrial structure adjustments (Wang et al., 2011; Niu et al., 2016; Cui et al., 2019).

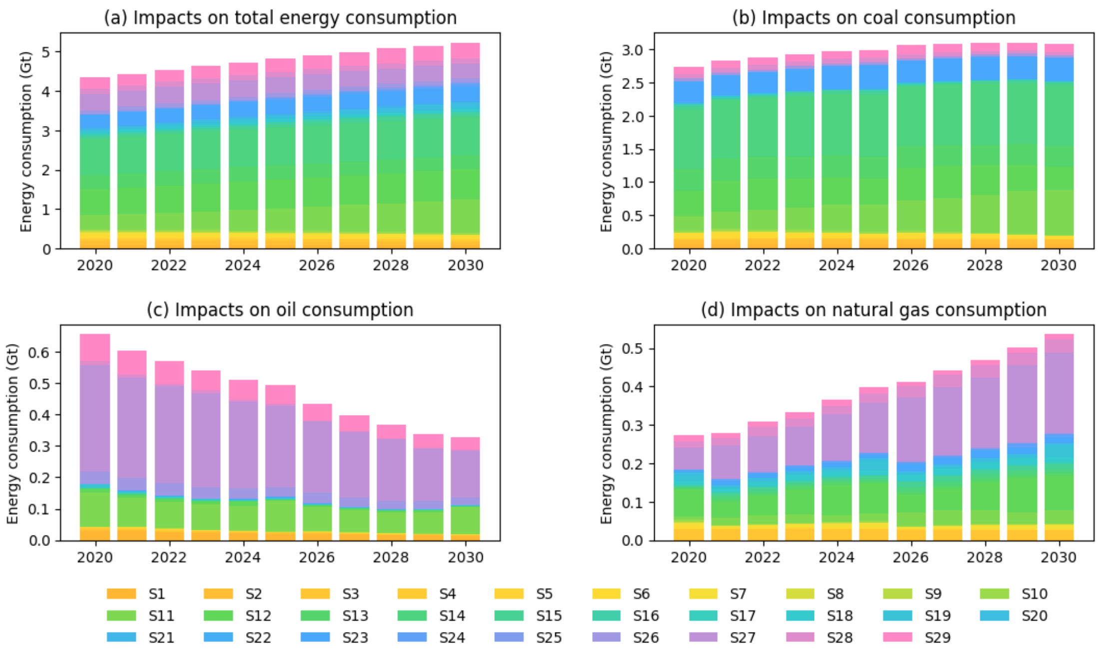

Figure 6-4 The sector-level impacts on energy consumption based on input-output future configuring system of China

For impacts on coal consumption, the scope of sectors consuming 80% of coal will shrink from 2020 to 2030. That is, the number of the sectors consuming 80% of coal will decline from 6 to 5. The first three sectors using 80% of coal will change in 2030. For instance, the first three sectors were sectors 14 (*Manufacture and Processing of Metals*), 12 (*Manufacture of Chemicals and Chemical Products*), and 13 (*Manufacture of Plastic Products*) in 2020, but they will change to sectors 14, 11 (*Manufacture of Refined Petroleum, Coke Products, Processing of Nuclear Fuel*), and 12 in 2030. Also, as the number of sectors consuming 80% of coal will decrease, sectors 14, 11, and 12 will turn to be more important for coal consumption. These results indicate that continuing the structural shift from reliance on high-coal-intensive sector to dependence on high-electricity-intensive sectors is advocated (Lin et al., 2018). Also, improving energy intensity and adjusting energy consumption structure are advocated for reducing coal consumption (Chai et al., 2019).

For impacts on oil consumption, the scope of sectors consuming 80% of oil will shrink from 2020 to 2030, and the number of these sectors will decrease from 4 to 3. But at the same time, the first three sectors using 80% of oil will be unchanged during 2020-2030. That is, in 2020, the first three sectors using 80% of oil were sectors 27 (*Transport, Storage and Post*), 11 (*Manufacture of Refined Petroleum, Coke Products, Processing of Nuclear Fuel*), and 29 (*Other Services*). In 2030, the first three sectors using 80% of oil will still be sectors 27, 11 and 29. To promote the better use of oil, controlling total oil consumption, enhancing oil saving, and increasing investment on oil exploitation and oil refining are suggested (Ma et al., 2012; W.-Q. Li et al., 2015). Also, when considering the larger increase in the oil use of sector 11, the research and spread of energy-saving technologies is valued as far as the energy efficiency improvement of sector 11 is considered (Xie et al., 2016).

For impacts on natural gas consumption, the scope of sectors consuming 80% of natural gas will shrink during 2020-2030. That is, the number of sectors using 80% of natural gas will decrease from 8 to 7. Also, the first three sectors using 80% of natural gas will change from 2020 to 2030. In 2020, the first three sectors using 80% of natural gas were sectors 12 (*Manufacture of Chemicals and Chemical Products*), 27 (*Transport, Storage and Post*), and 3 (*Extraction of Crude Petroleum and Nature Gas*). But in 2030, the first three sectors using 80% of natural gas will be sectors 27, 12, and 11 (*Manufacture of Refined Petroleum, Coke Products, Processing of Nuclear Fuel*). To promote the better use of natural gas, efforts from natural gas production and consumption are considered comprehensively (Cui et al., 2019; Y. Wang et al., 2021). Efforts from natural gas production include deepening natural gas cooperation, further strengthening the construction of natural gas transportation pipelines, and improving natural gas supply and transportation capacity. Also, efforts from natural gas consumption include cultivating natural gas market to replace coal and fuel gas, promoting the use of natural gas in the field of transportation, and promoting the use of natural gas vehicles.

6.4.3.3. The impacts on CO_2 emissions

Figure 6-5 shows the sector-level impacts on total CO_2 emissions, and CO_2 emissions from coal, oil and natural gas in China from 2020 to 2030, which is based on input-output future configuring system. For impacts on total CO_2 emissions, the scope of sectors emitting 80% of total CO_2 emissions will be unchanged from 2020 to 2030. That is, the number of sectors emitting 80% of total CO_2 emissions will maintain stable at 3 and these sectors will still be sectors 23 (*Production and Supply of Electricity and Steam*), 14 (*Manufacture and Processing of Metals*), and 13 (*Manufacture of Plastic Products*) in 2030. Also, CO_2 emissions from sector 23 will increase during 2020-2030, while those from sectors 14 and 13 will peak in the years 2027 and 2020 respectively. These results indicate that most of total CO_2 emissions will continue being from energy-intensive sectors. To address this issue, related countermeasures are advocated (Du et al., 2018), such as promoting industrial agglomeration to make full use of scale effect, improving energy efficiency through technological progresses, reinforcing energy conservation, and strengthening industrial upgrading.

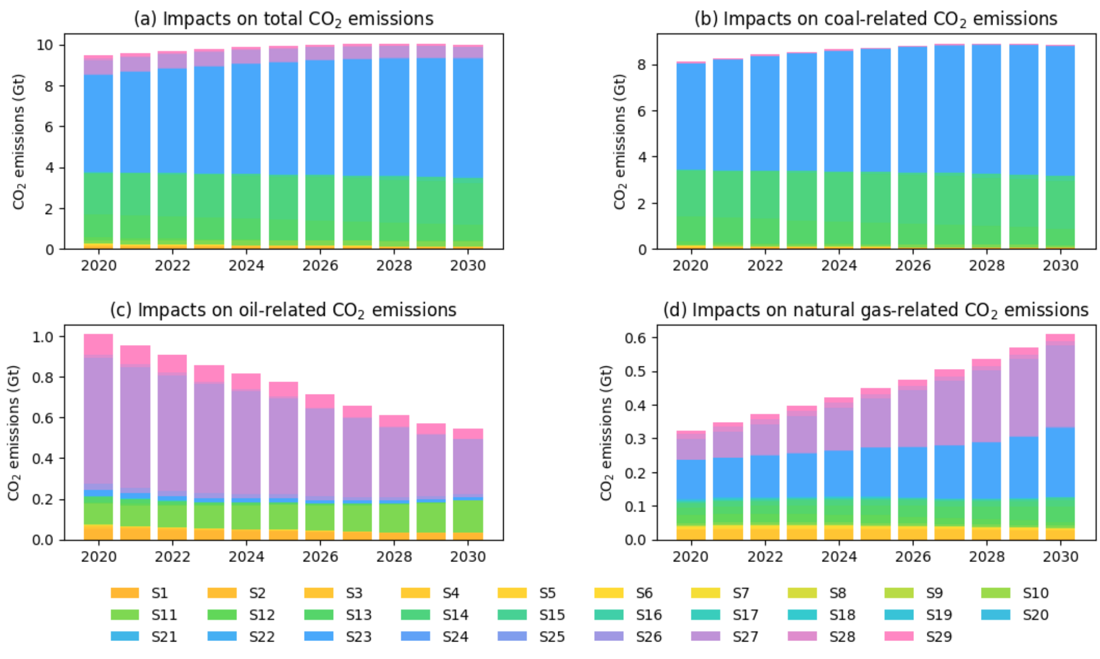

Figure 6-5 The sector-level impacts on CO_2 emissions based on input-output future configuring system of China

For impacts on coal-related CO_2 emissions, the scope of sectors emitting 80% of CO_2 emissions will sustain stable from 2020 to 2030. That is, the number of sectors emitting 80% of CO_2 emissions will be maintained at 2. These sectors include sectors 23 (*Production and Supply of Electricity and Steam*) and 14 (*Manufacture and Processing of Metals*). CO_2 emissions from sectors 23 and 14 will peak in the years 2029 and 2026, respectively. To reduce coal-related CO_2 emissions, a low-carbon energy consumption structure, technologies for utilizing coal with high efficiency and low pollution, and energy-conserving requirements and support are supposed to be continuously put efforts on (Y. Wang et al., 2021).

For impacts on oil-related CO_2 emissions, the scope of sectors emitting 80% of CO_2 emissions will be stable from 2020 to 2030, and the number of sectors will be maintained at 3. The sectors emitting 80% of CO_2 emissions will be unchanged, which include sectors 27 (*Transport, Storage and Post*), 11 (*Manufacture of Refined Petroleum, Coke Products, Processing of Nuclear Fuel*), and 29 (*Other Services*) in 2030. CO_2 emissions from sector 27 will peak in the year 2020 and sector 29 will follow this trend. On the contrary, CO_2 emissions from sector 11 will increase from 2020 to 2030. Against the backdrop of CO_2 emissions limits, oil emission regulation will have greater influence on long-term oil development (Ma et al., 2012). Also, the de-carbonization of oil, a radical shift of fuels from fossil-based oils to clean alternatives, and a set of incentives market-based schemes supporting this shift would be essential (Jiang et al., 2019c; Wang et al., 2023).

For impacts on natural gas-related CO_2 emissions, the scope of sectors emitting 80% of CO_2 emissions will shrink from 2020 to 2030. That is, the number of sectors emitting 80% of CO_2 emissions will decrease from 6 to 3. Then, the first three sectors emitting 80% of CO_2 emissions in 2030 will change. In detail, these sectors were sectors 23 (*Production and Supply of Electricity and Steam*), 27 (*Transport, Storage and Post*), and 3 (*Extraction of Crude Petroleum and Nature Gas*) in the year 2020. Then, the first three sectors will change to sectors 27, 23 and 13 (*Manufacture of Plastic Products*) in the year 2030. CO_2 emissions from these sectors will increase during 2020-2030. For the development of low-carbon energy, natural gas has been attached increasing attention in China. The continuous efforts in promoting natural gas development are needed for CO_2 emissions reduction (Qin et al., 2018; G.-J. Zhang et al., 2019), including the improvement of natural gas layout and utilization system, the increasing investment in domestic natural gas exploration and development, the facilitation of natural gas market reform, the enhancement of core technology research, and the improvement of relevant laws and regulations.

6.5. Conclusion

Input-output optimization for forecasting has attracted increasing interest in the context of LCE study. To reflect and reconcile the future trends in the context of LCE, we propose an input-output future configuring system for LCE. This system is constructed by a SAM optimization design, which is achieved within the CGE-based framework. During the system construction, optimum designs are conducted for LCE performance and planning-based parameter setting. A CGE appraisal framework is integrated into optimization. This system is validated through Monte Carlo simulations. When applying this system to the context of LCE, a new method is proposed through combining the element-based Fourier-Markov method (EFM) with the simultaneous equations method (SEM), so as to analyse the impacts of future trends on economy, energy and CO_2 emissions and suggest countermeasures correspondingly. This study is in the case of China from 2020 to 2030.

The validation results show that the uncertainty level of this system is low and stable from 2021 to 2030. At the aggregate level, the Z-scores of the lower bound of uncertainties are around -1.965; meanwhile, the Z-scores of the upper bound of uncertainties are around 1.952. At the economic activity level, Z-scores are distributed stably with the median lines maintaining around the Z-score of -0.314 and the interquartile range from -0.555 to 0.138. Similarly, at the economic transaction level, Z-scores are distributed stably, with the median lines sustaining around the Z-score of -0.149 and the interquartile range from -0.153 to -0.118. Besides, the economic activity contributing most to the uncertainty is the economic activity 46 (*Urban Household account*), and the economic transaction generating the largest uncertainty is the economic transaction from economic activity 52 (*Others account*) to economic activity 50 (*Capital Factor account*).

Regarding the reflection and reconciliation of future trends of LCE, the main results are summarized as follows. At the aggregate level, keeping the current economic development mode will continue generating multiple benefits. Adjustments are still needed for the changes that will be experienced by energy consumption structure. Continuous efforts are advocated in addressing coal-related CO_2 emissions for effectively promoting the reduction of CO_2 emissions. At the sector level, the impacts of future trends on economy, energy and CO_2 emissions provide the interdisciplinary viewpoints for LCE development. In the meantime, the sector heterogeneity is found in the abovementioned impacts. Combining the interdisciplinary viewpoints with the sector heterogeneity could provide a reference for the countermeasures of CO_2 emissions reduction at sector level.

Chapter 7: Conclusion

Input-output table (IOT) and social accounting matrix (SAM) are two interconnected but unique input-output systems in the area of economy. Constructing time-series input-output tables (IOTs) and social accounting matrices (SAMs) could attain two tipping points. One is concerned with tracing the structural trajectories of economic systems from past to future. The other is with regard to rendering economic systems analytical dynamically and effectuating the explorations of various external variables from the time dimension. Further, environmentally extending time-series IOTs and SAMs with newly proposed techniques could be considered as meaningful feedbacks for the development of time-series input-output systems.

Favourable endeavours have been devoted to constructing time-series IOTs and SAMs, and, correspondingly, to exploring carbon development measures. However, increasing attention could be drawn to the role of utilizing and exploiting the fundamental and important features of input-output systems in achieving these two tipping points. This consideration promotes the methods improvements of this thesis (Section 7.1). To realize the real-world importance of these methods improvements, this thesis is in the case of China and the period of research spans from 1997 to 2030. The results gained (Sections 7.2 and 7.3) include the time-series table series for IOTs, SAMs and CO_2 inventories, as well as carbon implications. On the basis of these methods improvements, future research could be initiated and conducted with an aim of achieving the progressions of necessity and importance (Section 7.4).

7.1. Summary of methods improvements

(1) Updating time-series input-output tables with economic structure concerns and identifying CO_2 clusters changes. Time-series input-output tables (IOTs) elaborate economic structures over time. In this study, we therefore utilize economic structure concerns to update time-series IOTs. A new matrix calculation method is proposed for tracking and establishing matrix-based links among intermediate input-outputs, final demand and value added. The method is reinforced by reflecting price fluctuations in IOTs. This method is further extended by proposing a matrix-based linking method to trace the structure changes of final demand and value added. The validation analysis of time-series IOTs is conducted using Monte Carlo simulations in the context of the matrix-based structures of IOTs. Based on the time-series IOTs, CO_2 clusters changes from production, consumption and income perspectives are identified, deriving sector characteristics to reduce CO_2 emissions. This study is in the case of China from 1997 to 2020.

(2) A forward-backward realization of solutions to time-series social accounting matrices construction, validation and applications. Social accounting matrix (SAM) elucidates the economic transactions flowing forward and backward, thereby forming a matrix-based structure. This feature is exploited, constituting a forward-backward realization of solutions to time-series SAMs construction, validation and applications. In this study, the matrix-induced structure features time-series SAMs construction, during which K-nearest-neighbour algorithm and leave-one-out cross-validation are joint to handle missing data. Also, a new matrix calculation method is proposed to conduct time-series SAMs validation in terms of gauging the economy-wide effects of each economic agent. Using time-series SAMs, both demand-driven and supply-driven CO_2 emissions are analysed and compared by extending multiplier decomposition analysis and structural path analysis. This study is in the case of China from 1997 to 2020.

(3) Input-output forecasting and CO_2 inventories construction using a new subsystem decomposition analysis. Forecasting IOTs and SAMs is an attempt to trace the trends inherent in the economic system, and to render the economic system analytical when exploring the future of various external variables. In this study, we therefore propose a procedure of input-output forecasting. During this procedure, the input-output table series are forecasted by way of an element-based Fourier-Markov model, then structured through modified matrix transformation technique and T-accounts concept, and last, validated by combining matrix calculation methods with Monte Carlo simulations. On the basis of the forecasted table series, we construct CO_2 inventories by proposing a new integrated method, that is, the combination of subsystem analysis with structural decomposition analysis. With this method, CO_2 inventories quantify historical and future emission channels throughout the economic system from demand and supply sides, and then account for the contributions of influencing factors behind temporal changes in emission channels. This study is in the case of China from 1997 to 2025.

(4) An integrated scheme of input-output future scenarios construction interconnecting production with consumption and sector-level CO_2 emissions synergistic alleviation. In response to the explorations of prospective trajectories, input-output analysis (IOA) in a scenario context could encompass intra- and inter-sector linkages in future scenarios, and also investigate the potential pathways of external variables. When integrating IOA and scenario analysis, multi-criteria decision making techniques have been found to be feasible and useful. Against this backdrop, we propose an integrated scheme of input-output future scenarios construction to help alleviate CO_2 emissions in a holistic manner. That is, we set up three categories of input-output future scenarios by interconnecting production with consumption. In detail, we start input-output BAU scenario through a procedure of input-output forecasting. We then construct input-output policy-related scenario by extending the multi-objective optimization method with multiple policy-related parameters. We finally arrange input-output problem-specific scenarios using multi-attribute decision making which incorporates the generalized weighting method into the permutation and combination method, and supports the construction of a multi-attribute importance method. Within the three constructed categories of input-output future scenarios, sector-level CO_2

emissions synergistic alleviation is analysed. This study is in the case of China from 2020 to 2030.

(5) Input-output future configuring system for low-carbon economy using a social accounting matrix optimization design. To reflect and reconcile the future trends in the context of low-carbon economy (LCE), this study proposes an input-output future configuring system for LCE. This system is constructed by a social accounting matrix optimization design, which is achieved within the computable general equilibrium (CGE)-based framework. During the system construction, optimum designs are conducted for LCE performance and planning-based parameter setting. Then, a CGE appraisal framework is integrated into optimization. Also, this system is validated through Monte Carlo simulations. When applying this system to the LCE context, a new method is proposed through combining the element-based Fourier-Markov method with the simultaneous equations method, so as to analyze the impacts of future trends on economy, energy and CO_2 emissions are analyzed and suggest countermeasures correspondingly. This study is in the case of China from 2020 to 2030.

7.2. Summary of time-series tables

7.2.1. Time-series IOTs from retrospect to prospect in China

The time-series IOTs illustrate the economic structure of China from 1997 to 2020. These series of IOTs were constructed in a uniform format: in the row direction, each IOT consists of an intermediate input-output matrix (42*42), a final demand matrix (42*7), and a total output vector (42*1); in the column direction, besides the same intermediate input-output matrix (42*42), other matrices compose each IOT, including an import matrix (1*49), a value added matrix (4*42), and a total input matrix (1*42). For each IOT, the intermediate input-output matrix represents the intermediate input-outputs among 42 sectors; the final demand matrix is composed of rural household consumption, urban household consumption, government consumption, capital formation, changes in inventories, exports and others; and the value added matrix contains compensation of employees, net taxes on production, depreciation of fixed capital, and operating surplus. Besides, the time-series IOTs are represented at 1997 constant prices and at current prices, respectively.

7.2.2. Time-series SAMs from retrospect to prospect in China

The time-series SAMs illustrate the economic transactions and transfers among economic agents from 1997 to 2020 in China. These series of SAMs are constructed in a uniform format. Each SAM is a 52*52 square matrix: the 52 economic agents in the row direction are consistent with those in the column direction; meanwhile, the distributive and redistributive processes of transactions flows among these 52 agents are documented. Additionally, the 52 economic agents are categorized into the following blocks: (1) the production block (including 42 industrial sectors); (2) the factor block (including labour and capital factor accounts); (3) the institution block (including rural household, urban household and enterprise accounts); (4) the government block; (5) the rest of world block; (6) the investment block; (7) the inventory block; and (8) the others block. Besides, the time-series SAMs are represented at 1997 constant prices and at current prices, respectively.

7.2.3. China's CO_2 inventories using a new subsystem decomposition method

The CO_2 inventories are clarified into four categories, which depict the contributions of 11 influencing factors behind temporal changes in sector-level CO_2 emissions transmitting throughout the IOT- and SAM-related production systems in the contexts of demand-driven and supply-driven models. In the meantime, the CO_2 inventories span a period of time from 1997 to 2025, describing the past from 1997 to 2020 and the forecasts from 2021 to 2025. According to Table 1, each CO_2 inventory is in a uniform format and is a $n * 11$ matrix. In the row direction, there are 11 items to inform the contributions of 11 influencing factors to the emissions changes of each sector. In the column direction, the emissions changes arising from each of the aforementioned 11 items are distributed among n sectors.

7.3. Summary of carbon implications

7.3.1. CO_2 clusters changes from multiple perspectives

With the time-series IOTs constructed, changes in CO_2 clusters from production, consumption and income perspectives are identified, deriving and utilizing sector characteristics to reduce CO_2 emissions. First, the role of economic structure optimization is emphasized in CO_2 emissions reduction from production, consumption and income perspectives; meanwhile, during the economic structure optimization, the possible lock-in, catch-up and unlocking effects need attention. Second, to reduce CO_2 emissions, sector-level plans and roadmaps are highlighted from production perspective, sector-level CO_2 emissions reduction measures attaching importance to final demand affecting CO_2 emissions could be feasible from consumption perspective, and the income perspective supports that the measures proposed from multiple perspectives could be considered together for identified sectors besides providing perspective-specific measures. Third, preserving and proactively promoting sustainable consumption is necessary for reducing CO_2 emissions driven by urban household consumption. Last, tracking the strongest paths derived from CO_2 clusters from demand and supply sides could provide the channels with most potentials of enhancing the efficacy of CO_2 emissions reduction.

7.3.2. CO_2 emissions from MDA and SPA

Using the time-series SAMs constructed, demand- and supply-driven CO_2 emissions provided different insights at multiplier effect, tier and path levels for CO_2 emissions reduction. In the demand-driven case, more attention could be put on reducing the transfer and closed-loop multiplier effects at the aggregate and sector levels, decreasing the impacts from tiers 1 and 2 with the consideration of sector heterogeneity, and tackling the potential lock-in effects of the crucial paths. On the contrary, in the supply-driven case, more attention could be attached to reducing the closed-loop and open-loop multiplier effects from both the aggregate and sector viewpoints, decreasing the impacts from tiers 2 and 3 with the concern of sector heterogeneity, and tackling the increasing influences of the crucial paths. But there are also common implications derived from these two cases: CO_2 emissions reduction measures could consider the need for coping with the potential lock-in and increasing effects of CO_2 emissions, and selecting the crucial paths as pilot paths to alleviate the CO_2 emissions attributed to different tiers could be a way to reduce CO_2 emissions effectively and efficiently.

7.3.3. CO_2 emissions from subsystem analysis and SDA

On the basis of time-series IOTs and SAMs from retrospect to prospect, the main results concerning demand- and supply-driven CO_2 emissions from subsystem analysis and SDA are summarized as follows. First, the spillover component was the largest determinant of CO_2 emissions and is forecasted to continue this tendency. Second, the final demand (or value-added) remained and are projected to be the factor contributing most to emissions increases in the demand-driven model (or supply-driven model). Third, the effects of other influencing factors to emissions changes differed and are forecasted to differ, depending on the type of input-output system, and whether the model is demand-driven or supply-driven. Last, the sector-level performance is forecasted to be different for each category of CO_2 inventories, but the sector-level analysis by way of the maximum and minimum measurements of CO_2 emissions changes could provide supports for the carbon abatement across all sectors. Accordingly, the main carbon implications are proposed as follows. First, it is of necessity to continue and update the supply chain management in moderating the level of CO_2 emissions. Second, measures, related to the optimization of final demand and the reasonable use of primary inputs, could be effective in alleviating CO_2 emissions. Third, exploiting the potentials of other selected influencing factors (e.g., emissions intensities, inter-sector technological levels, and inter-sector allocation relations) could be feasible for reducing CO_2 emissions. Last, corresponding to the idea of sector-level analysis introduced in section 4.3.5, as for each of the 11 influencing factors, the sector-specific experience of decreasing CO_2 emissions could be generalized and shared among sectors.

7.3.4. CO_2 emissions within input-output future scenarios

Regarding CO_2 emissions synergistic alleviation within the input-output future scenarios, there are several main results and implications. First, the scenarios where peak CO_2 emissions are achieved are identified, which indicates that additional measures for CO_2 emissions reduction are needed. Second, among the identified contexts, the structures of CO_2 emissions in 2030 do not experience large changes and maintain the similar pattern to the 2020 level, which emphasizes that CO_2 emissions reduction is expected to continue focusing on the efforts of specific sectors. Third, for the economy-wide effects of CO_2 emissions alleviation, the changes of CO_2 emissions suggest the importance of reallocating CO_2 changes among sectors in a holistic manner. Fourth, the timetable derived from each scenario selected could not only earmark the adjustments in the sectoral policies of CO_2 emissions reduction, but also could provide a reference for formulating the measures of alleviating CO_2 emissions at sector level. Finally, the overall and dynamic changes in CO_2 emissions using SSA inform the directions and channels for CO_2 emissions reduction at sector level, and provide a reference when the synergistic deployment of CO_2 emissions alleviation among sectors is implemented and the sequential peaking of CO_2 emissions among sectors is promoted.

7.3.5. CO_2 emissions from the perspective of future trends of LCE

Regarding the reflection and reconciliation of future trends of LCE, the main results are summarized as follows. At the aggregate level, keeping the current economic development mode will continue generating multiple benefits. Adjustments are still needed for the changes that will be experienced by energy consumption structure.

Continuous efforts are advocated in addressing coal-related CO_2 emissions for effectively promoting the reduction of CO_2 emissions. At the sector level, the impacts of future trends on economy, energy and CO_2 emissions provide the interdisciplinary viewpoints for LCE development. In the meantime, the sector heterogeneity is found in the abovementioned impacts. Combining the interdisciplinary viewpoints with the sector heterogeneity could provide a reference for the countermeasures of CO_2 emissions reduction at the sector level.

7.4. Limitations and future research

Although the above-mentioned summaries investigate the improvements in terms of methodology, data and implications, this thesis has some limitations. Such limitations are critically reviewed and suggestions for future research are provided.

First, the methods for constructing time-series input-output systems and exploring carbon development measures are limited to single-region applications, which could be extended directly to the multi-region context for future research. It is because these methods are based on the IOT- or SAM-related frameworks which are suitable for both single- and multi-regional contexts (Zhang and Zhao, 2007; Mi et al., 2018b; Zheng et al., 2021; Seung, 2014b). Thus, time-series multi-regional IOTs and SAMs could be updated. At the same time, a single-region perspective could make sense when the sector-level carbon development experiences are applicable across regions (Zheng et al., 2014; J. Wang et al., 2021). For example, each particular sector within energy-intensive industries has similar technical characteristics (J. Wang et al., 2019). For another example, there exists the debate between region- and industry-based approaches to reducing CO_2 emissions (Wei et al., 2012). The industry-based approach meets the requirements of macro-level planning and satisfies the demand of the domestic carbon market in the future. The region-based approach takes into consideration the unbalanced development among regions for CO_2 emissions reduction.

In these regards, sector-level characteristics could contribute to the efficiencies and effectiveness of CO_2 emissions reduction. Despite that, it is meaningful and of vital importance that the related carbon development measures are explored from a multi-regional perspective. This is because the multi-regional input-output models could function as a tool for national and regional planning through demonstrating inter-regional and inter-sectoral economic flows (Mi et al., 2018b), and provide practical portfolios for CO_2 emissions abatements (Mi et al., 2017a; H.-R. Zheng et al., 2020).

Second, the methods for constructing time-series input-output systems and exploring carbon development measures are limited to the case of CO_2 emissions, which could be extended to other interdisciplinary fields (e.g., metals, water, and materials) for future research. It is because these methods are also feasible when converting the economic flows into the flows of other fields (S. Liang et al., 2015; Acquaye et al., 2017). For one thing, the constructed time-series IOTs and SAMs could provide data supports for experimental studies from the time dimension, which is helpful in generating relevant plans and achieving long-term goals (Hartono and Resosudarmo, 2008; Akkemik, 2012; Chen et al., 2022). For another, the carbon development measures explored could provide a reference for the development of other interdisciplinary fields. For example, the new subsystem decomposition method proposed in Chapter 4 could be used in a straightforward manner for constructing water consumption inventories, which further helps improve water security and sustainability (Cazcarro et al., 2013; S.-D. Zhang et al., 2019; Zhao et al., 2021). In these regards, the interdisciplinary insights on the basis of the methods in this thesis could get emphasized and promoted.

Last, the methods for constructing time-series input-output systems and exploring carbon development measures focus on IOT- and SAM-related frameworks which are typical systematic constructs. That means, when other input-output systems are established, IOT- and SAM-related schemes are supposed to be adjusted to suit and to develop collaborative connections with these input-output systems. For example, the new forms such as the environmentally extended IOT- and SAM-based constructs could be developed (Leontief, 1970; Schäfer and Stahmer, 1989; Li and Ikeda, 2001). Further, these new forms provide data supports for the data envelopment analysis (DEA) method in the field of sustainability, so as to assess the impacts of specific influencing factors on sustainability (Cheng et al., 2019; Wang et al., 2022) and to specify the preplanning as well as preparedness for sustainable development (Z. Li et al., 2018; Zheng and Xu, 2020). For another example, when conducting the research about how sustainable development goals will be achieved, IOT- and SAM-related frameworks could be incorporated into the system dynamics (SD) model (H.-P. Huang et al., 2019; Wu et al., 2014; Lim et al., 2019), which is conductive to improving the systematic behaviors through analyzing the interconnected strategic problems in their interconnected contexts (Saysel et al., 2002; H. Liu et al., 2015; Zhao et al., 2018).

Appendices

Appendix Table 1: The structure of competitive input-output table

Input \ Output		Intermediate use				Final consumption						Import	Total output
		Sector 1	Sector 2	…	Sector n	Rural household	Urban household	Government	Gross fixed capital formation	Changes in inventories	Export		
Intermediate use	Sector 1			…									
	Sector 2			…									
	…	…	…	…	…	…	…	…	…	…	…	…	…
	Sector n			…									
Value added	Compensation			…									
	Net taxes			…									
	Depreciation of fixed assets			…									
	Operating surplus			…									
Total input				…									

Appendix Table 2: The structure of non-competitive input-output table

Output / Input		Intermediate use				Final consumption						Total output
		Sector 1	Sector 2	…	Sector n	Rural household	Urban household	Government	Gross fixed capital formation	Changes in inventories	Export	
Intermediate use	Sector 1			…								
	Sector 2			…								
	…	…	…	…	…	…	…	…	…	…	…	…
	Sector n			…								
Import				…								
Value added	Compensation			…								
	Net taxes			…								
	Depreciation of fixed assets			…								
	Operating surplus			…								
Total input				…								

Appendix Table 3: The structure of social accounting matrix

		Expenditures									
		Activities	Labour factor	Capital factor	Household	Enterprise	Government	Rest of world	Capital account	Inventory	Others
Receipts	Activities	Intermediate goods			Household consumption		Government expenditure	Export	Capital formation	Stock changes	Others
	Labour factor	Wages									
	Capital factor	Profits									
	Household		Wages	Factor income		Corporation income	Government transfers and subsidies	Foreign transfers			
	Enterprise			Factor income							
	Government	Net taxes			Household taxes	Enterprise taxes		Foreign transfers	Debt revenue		
	Rest of world	Import		Factor income			Government transfers				
	Capital account				Household savings	Enterprise savings	Government savings	Foreign savings			
	Inventory								Stock changes		
	Others								Others		

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