RESEARCH ARTICLE

Research on economic and social impact of carbon emissions in the construction industry at a regional scale: a case of Shandong, China

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Abstract

To identify the impact of carbon emissions in the construction industry on the society and economy at a regional scale is of great significance for the sustainable development of the construction industry. Taking Shandong, China, as an example, this study uses a process-based carbon emission assessment method to calculate the carbon emissions of the construction industry in Shandong from 2010 to 2020. Based on specific situations at different phases, ten major factors affecting the society and economy have been analyzed and identified. Then, the Seemingly Uncorrelated Regression (SUR) model was used to analyze carbon emissions and economic and social factors at each stage. The results show the following: (1) The overall carbon emissions of the construction industry in Shandong are on an increasing trend, the carbon emission intensity is on a decreasing trend, and the material production and operation stages are the main source of carbon emissions; (2) There is a significant relationship between carbon emissions in the construction phase and all influencing factors, so it should be the main phase for macro-regulation; (3) Unlike in the Ordinary Least Square (OLS) model, the error terms of the gross output value of the construction industry and the total turnover of the main building materials equations are independent; however, there is an interaction between the error terms of the remaining equations. The results provide a theoretical reference for governmental departments to set up environmental targets and make policy regulations.

Nomenclature

ADF	Augmented dickey-fuller
ANPC	Average number of persons engaged in construction activities
AWC	Average wage of construction workers
CECI	Carbon emissions in the construction industry
CEI	Carbon emission intensity
CRE	Construction industry research and experimental development funds
ECPA	Energy consumption per unit construction area
GNP	Gross national product
GOVC	Gross output value of the construction industry
LCA	Life cycle assessment
LCSA	Life cycle sustainability of buildings assessment
OLS	Ordinary least square mode
OMPI	Operation and maintenance price index
PHG	Proportion of households with a green landscape in the community
PIBH	Price index of building materials and hardware
RMSE	Root mean squared error
PROV	Profit rate of output value
SUR	Seemingly uncorrelated regression model
TTB	Total turnover of primary building materials

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Introduction

Over recent years, many countries have increased efforts to reduce emission of greenhouse gas, the most dominant component of which is CO_2. Excessive emissions of greenhouse gas can lead to many problems, including sea level rise,

extreme weather, and seawater acidification. At the 2015 Paris Climate Conference, many countries agreed to commit to reducing domestic carbon emissions (UNFCCC 2015). Also at the conference, China renewed its commitment to reaching carbon peaking by 2030; in fact, it has worked to achieve this goal ahead of schedule (B Li et al. 2020a, b). It is shown that CO_2 emissions from the construction sector account for 27.9–34.3% of the total carbon emissions in China (Shi et al. 2017), and so it is a crucial industry and has great potential for carbon reduction in China (Lin and Liu 2015; Hossain and Poon 2018; Guo et al. 2019). While consuming a large number of natural resources and energy throughout the whole process, the construction industry generates a large amount of pollution, which has imposed an impact on the economic and social development to a certain extent. Unfortunately, few studies have explored such impact from the construction industry.

As a country with extensive and diversified geographical areas, China sees large differences in economic levels and energy structures among its provinces. Therefore, carbon emission reduction in the construction industry and the economic and social development are a complex and systemic issue. By analyzing the influencing factors of carbon emissions in the construction industry at the provincial level, some researchers have found certain relevant and realistic relationship (Li et al. 2015). Most scholars have focused on carbon emission calculation methods to search for carbon emissions' impact factors, but few have paid attention to the systematic analysis of the impact of carbon emissions in the construction industry (CECI) on the economy and society at the provincial level (Xie 2014; Wang et al. 2017; Du et al. 2019b). Given that as early as in 2009, the Chinese government had pledged that by 2020, it would reduce its CO_2 intensity per unit of GDP by 40–45% from the level in 2005 (Zhou et al. 2013). This study would calculate the carbon emissions of the construction industry in Shandong Province during 2010–2020 by making a reference to the process analysis method proposed by Zhang and Wang (2017). In addition, through literature review and expert interviews, this study has finally identified ten leading factors that influence the economy and society through carbon emissions at different stages. Subsequently, by using the augmented dickey-fuller (ADF), the cointegration test, and the SUR and OLS comparison analysis, this study reveals the impact of carbon emissions on the economy and society in the whole life cycle of the construction industry.

The novelties and contributions of this study can be summarized as follows: (1) In the process of carbon emission calculation for buildings, the impact of carbon emissions on the economy and society at each stage is deeply explored and analyzed through literature review, expert interviews, and conversion of the impact factors into data-available ten indicators to facilitate scientific data analysis. (2) In

each regression equation, both the existence of a specific correlation between the dependent variables and the existence of certain random perturbation factors are considered, with a SUR model established. As a result, the influence of uncertainties is reduced and the accuracy of the outcomes is improved; and (3) by using model analyses, this study clarifies the impact of carbon emissions on the economy and society as well as the linkages between them at each stage. The results of this study can help the Shandong government and related departments understand the state of CECI of the province, while providing theoretical references for macro-regulation and target setting.

Literature review

Currently, the research on carbon emission calculation can be divided into three main patterns, top-down, bottom-up, and hybrid of the two (Du et al. 2019a). The main idea of the top-down calculation method is to start from a general objective and then decompose it into as much detailed data as possible, so as to build a systematic model. This method is widely used at the macro level. The most usual example of this method is the input–output approach. For instance, Nassen et al. (2007), Acquaye and Duffy (2010), and Chen et al. (2017) have calculated the CECI in Sweden, Ireland, and China, respectively, by using the top-down input–output approach, finding that indirect carbon emissions play a dominant role. Wang et al. (2017) and Xie (2014) have further studied the influencing factors by using the indicator and structural decomposition analysis. Generally, the top-down approach performs well in economic energy analysis, especially in specific descriptive analysis. In contrast, the bottom-up approach is to decompose a building deeply by starting from the carbon emission data of each process or each part and then aggregating all layers to get an overall picture of carbon emission of the building (Shorrock and Dunster 1997). Process-based analysis is a typical bottom-up approach, which is usually combined with life cycle assessment (LCA) and applied to micro-level analysis of carbon emissions of a single building. Peng (2016) has used a process-based LCA approach to analyze carbon emissions at each stage, finding that the operation stage has the highest carbon emissions, followed by the construction stage. Moon et al. (2014) have established a database of CO_2 emissions in the LCA method to calculate CO_2 emissions based on construction materials, with a reasonable accuracy of less than 8% error delivered in case studies. However, the bottom-up analysis method often leads to weak comparability between research results due to differences in life cycle divisions, emission boundaries, and carbon emission inventories. Given the shortcomings of the above two methods, some scholars have attempted to mix the two to simplify

the calculation process and enhance accuracy. By using the process method, Stephan and Stephan (2014) have calculated carbon emissions in the material production phase, while using the input–output approach to calculate carbon emissions in the remaining stages of residential buildings. Zhang and Wang (2016a) have developed a new method that can integrate the advantages of the process analysis and the input–output approach to calculate the implied carbon in the building construction segment. To further improve the hybrid method, Zhang and Wang (2017) have proposed a process-based method for assessing the life cycle carbon emissions of the construction industry in some Chinese regions. Assessing carbon emissions based on statistical data from relevant sectors, the method has been well practiced and can effectively support the calculation conducted in this study.

The economic-social impacts of CECI have been examined in the existing research. Some scholars have taken as a start point the life cycle sustainability of buildings assessment (LCSA), which is represented by three dimensions: environmental, social, and economic ones, commonly known as the Triple-Bottom Line. Onat et al. (2014) have analyzed the sustainability of the existing residential and commercial buildings in the USA by using the triple-bottom-line approach and a mixed economic input–output LCA model. Their research found that the operation phase, electrical energy, and transportation were crucial factors affecting sustainability. Llatas et al. (2020) have applied BIM and LCSA in the early design phase of some Spanish buildings, making contribution to the sustainable development. The difficulty in using LCSA for analysis lies in acquiring data on economic and social indicators, especially on social indicators (Dong and Ng 2016; Alberti et al. 2019; Zheng et al. 2019). To quantify these indicators, some researchers have attempted to incorporate related models into LCSA. For example, Hasheminasab et al. (2022) have applied a multi-criteria decision model to weigh the sustainability criteria and identify the structures and rankings of certain projects. Malmgren and Mjornell (2015) have proposed a rebuild decision-supporting method based on the Triple-Bottom Line to assess various renovation options for refurbishment projects. Some other studies have focused on analyzing the decoupling relationship between carbon emissions and economic output in the construction sector. For example, Du et al. (2019b) have analyzed the decoupling relationship between economic growth and carbon emissions in the construction sector across 30 Chinese provinces by using the standard deviation ellipsoid method, finding that the economic development levels in most of the provinces are positively correlated with their carbon emissions. Also focused on the construction sector in China, Wu et al. (2018) have examined the decoupling relationship between economic output and carbon emissions at the national and provincial

levels by using the Tapio decoupling model, with similar conclusions obtained.

In summary, a wealth of research on low-carbon and sustainable development in the construction industry provides theoretical support for this study. However, there are some limitations: (1) Although LCSA has been explored in-depth in the "triple baseline" dimension, very few studies have analyzed the economic-social impacts of carbon emission from the perspective of the construction industry; (2) Although the life cycle carbon emissions of the regional construction industry have been studied based on the process, the impacts on the economy and society have yet to be analyzed further; and (3) Although a few scholars have mentioned the impact on the economy and society in the process of carbon emission calculation, the interaction between the influencing factors has not been deeply analyzed.

To address the problems above, this study would, by calculating the CECI in Shandong from 2010 to 2020, profoundly explore the main factors influencing economic and social development, reveal the correlations among the influencing factors, and establish a SUR model to analyze the relationships. Then, it would put forward certain suggestions on the low-carbon development of the construction industry in the regional scope, so as to further enrich and boost relevant research.

Methodologies

In this study, the carbon emissions in the whole process of the construction industry were calculated in the process-based carbon emission calculation method. The literature relevant to the calculation process was reviewed, and the economic and social impact factors of carbon emissions throughout the life cycle of the construction industry were identified in the context of the United Nations Sustainable Development Goals and the Outline of the 14th Five-Year Plan (2021–2025) for National of the People's Republic of China Economic and Social Development and Vision 2035 of the People's Republic of China. The SUR model was used to analyze the relationships between these factors.

Calculation of the whole life cycle carbon emissions based on production processes

Based on the life cycle characteristics of a single building, the calculation of life cycle carbon emissions can be divided into three phases: the materialization phase (material production, transportation, and construction), the operation phase (daily operation of the building), and the demolition phase (demolition and transportation of the building). Carbon emissions can be measured in the process-based method, which quantifies carbon emissions based on the

data about the activities of carbon emission sources as well as the carbon emission factors at the corresponding unit activity levels. In reference to the whole life cycle carbon emission assessment method for the construction industry as proposed by Zhang and Wang (2017), carbon emissions can be calculated for six processes in three stages. The total carbon emissions are expressed as

$$CE = CEM + CEO + CED \tag{1}$$

where CE is the total life cycle carbon emissions; and CEM, CEO, and CED are the carbon emissions in the materialization, operation, and demolition phases, respectively.

Calculation of carbon emissions in the materialization phase

Carbon emissions in the materialization phase consist mainly of production, transportation, and on-site construction. They can be expressed as follows:

$$CEM = C_{pro} + C_{trans} + C_{cons} \tag{2}$$

$$C_{pro} = \sum_{i=1}^{n} \left(Q_i \times MF_i \right) \tag{3}$$

$$C_{trans} = \sum_{j=1}^{m} \left(\sum_{i=1}^{n} D_{i,j} \times Q_i \right) \times TF_j \tag{4}$$

$$C_{cons} = \sum_{g=1}^{r} \left(E_g \times EF_g \right) \tag{5}$$

where C_{pro}, C_{trans}, and C_{cons} denote the carbon emissions in the material production stage, transportation stage, and on-site construction stage, respectively. Q_i denotes the total weight of the i material. Only five materials are considered in this study: steel, cement, wood, glass, and aluminum. The data on material consumption were taken from the China Construction Industry Statistical Yearbook (National Bureau of Statistics 2021b). MF_i denotes the emission factor of the i material, and m denotes the number of transportation methods for construction materials. Given the properties of building materials, only three modes of transportation, i.e., railway, road, and waterway, are considered in this study. $D_{i,j}$ denotes the distance of transporting the i building material with the j transport mode. TF_j denotes the carbon emission factor of the j transport mode. The data on relevant transport distances were taken from the China Transport Yearbook (China Communications and Transportation Association 2021). The carbon emission factors of the three transport modes, i.e., railway, road, and waterway, are finally set to be 8.64, 284.14, and 37.28 $gCO_{2e}/(t\ km)$, respectively (Zhang

and Wang 2017). r denotes the number of types of energy consumed, and E_g denotes the consumption of energy g; and data on the energy consumption was taken from the China Energy Statistics Yearbook (National Bureau of Statistics 2021a). However, such data cover the energy consumption in the process of building demolition, accounting for about 9% of the on-site construction energy consumption (Zhang and Wang 2016a). Therefore, such energy consumption should be included in that of the demolition phase. EF_g denotes the carbon emission factor of energy g.

Calculation of carbon emissions in the operation phase

The data on carbon emissions in the operation phase were mainly obtained by converting the data on buildings' operational energy consumption, as expressed in the following equation:

$$CEO = \sum_{g=1}^{w} \left(E_g \times EF_g \right) \tag{6}$$

where w denotes the number of energy types involved in the operation phase, and other parameters are the same as in Eq. (5). The primary energy uses include heating, cooking, electrical appliances, lighting, and hot water (DZ Li et al. 2020a, b). The primary energy sources include electricity, coal, natural gas, coal gas, liquefied petroleum gas, gasoline, and diesel, the data on which were acquired from the China Energy Statistics Yearbook (National Bureau of Statistics 2021a).

Calculation of carbon emissions in the demolition phase

As stated in the "Calculation of carbon emissions in the materialization phase" section, 9% of the on-site construction energy consumption is for carbon emissions in the demolition phase. Waste transportation is calculated according to Eq. (4), assuming an average transport distance of 20 km (Zhang and Wang 2016b); and the weight of construction waste is estimated at 80% of the building materials (Liu 2015).

Economic and social impact factors of whole life cycle carbon emissions in the construction industry

To identify the economic and social impact factors of carbon emissions throughout the life cycle of the construction industry, the following background sources were adopted: the United Nations Sustainable Development Goals (UNSDG 2015); the Outline of the 14th Five-Year Plan (2021–2025) for National of the People's Republic of China Economic and Social Development and Vision 2035 of the People's Republic of China (General Office of the State Council

2021). In addition to this, detailed combination the "Calculation of the whole life cycle carbon emissions based on production processes" section and literature review (Karaca et al. 2020; Payyanapotta and Thomas 2021; Zhu et al. 2022). The preliminary economic and social impact indicators of CECI were identified, which include eight economic impact indicators: the total construction output, the output profitability, the cost of related materials, the total turnover of primary building materials, the energy consumption per unit of construction area, the operation and maintenance price index, the energy consumption of demolition construction, and the total transportation turnover of construction waste, and five social impact indicators: the research and technological development in the construction industry, the average wage of construction workers, the average number of people engaged in construction activities, the health and comfort of occupants, and the production of construction waste. These indicators are illustrated in Fig. 1. Since the following five indicators — the total output value of the construction industry, the profit margin of output value, the development of research and technology in the construction industry, the average wage of construction workers, and the average number of people engaged in construction activities — are related to the materialization phase, they are listed separately.

Typically, indicators should be applicable, understandable, and measurable (Haider et al. 2014); and similar indicators shall be aggregated to reduce the number of overlapped indicators. In this study, informal interviews were conducted with eight experts from universities, research institutions,

design agencies, development companies, construction experiment firms, suppliers, and government departments. Details of the interviews can be found in the Appendix. In these interviews, Experts 1 and 2 mainly suggested streamlining the indicators by merging similar ones and eliminating unimportant ones, such as the output of construction waste; Experts 3, 4, and 5 mainly proposed to quantitatively express the indicators accurately, while also mentioning the merging of similar indicators; Experts 6 and 7 suggested that the indicators should be optimized and expressed scientifically; and Expert 8 recommended that all the indicators related to transportation should be merged into one.

As the energy consumption in the building construction industry includes that for buildings' demolition, the energy consumption in demolition of construction was merged with the unit construction area energy consumption (Zhang and Wang 2017). In addition, given that the total turnover of primary building materials in the materialization phase and the total transportation turnover of construction waste in the demolition phase are two similar indicators, the eight experts unanimously suggested merging them. In order to facilitate data expression, Experts 3, 4, and 5 suggested referring to the Shandong Provincial Statistical Yearbook to replace the research and technology development of the construction industry with the research and experimental development funds of the construction industry, to replace the cost of related materials with the value index of construction materials and hardware and electrical materials, and to replace the health and comfort indicator of occupants with the proportion of households with green landscaping in the community. Experts 1, 2,

Fig. 1 Identification of the influencing factors
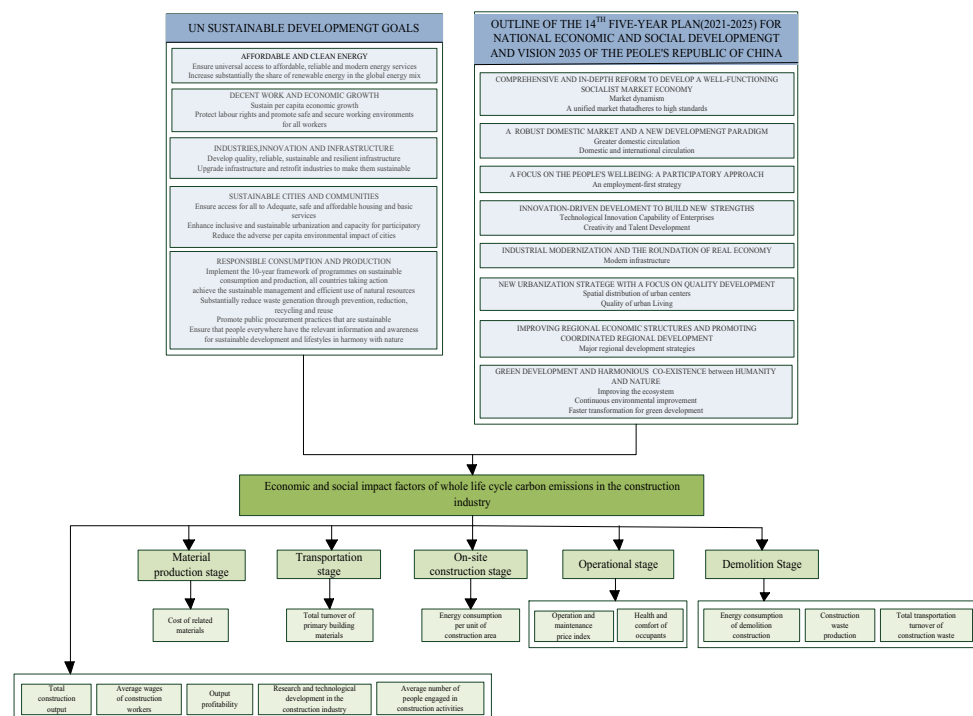
6, and 7 suggested deleting the indicator of construction waste produced due to the weak impact of the demolition stage in buildings' life cycle. Three indicators, i.e., gross construction output, output profitability, and research and technological development, were used for the whole construction industry, and these three indicators were classified into the materialization phase. Finally, the impact indicators were determined according to the experts' recommendations, as simplified and illustrated in Table 1.

Analysis methods

Modeling

The SUR model, first introduced by Zellner in 1962, is a set of multiple regression equations. It considers the correlation between equations and inter-equation errors in the parameter estimation, thus improving the parameter estimation effect compared to the traditional parameter estimation models, which only estimate parameters separately for each equation under certain appropriate conditions. Therefore, the SUR model can be used to explain the complex relationships embedded (Zellner 1962). As a result, the SUR model is considered appropriate for this study. A set of equations consisting of m seemingly unrelated linear regression equations are assumed in the SUR model, with a random set of regression equations expressed in Eq. (7).

$$y_i = \beta_i x_i + \varepsilon_i \quad i = 1, \cdots, m \tag{7}$$

where y_i is the vector of the explained columns in $m \times 1$ dimension; x_i is the matrix of the explanatory variables in $m \times p_i$ dimension; β_i is the vector of the unknown regression coefficients in $p_i \times 1$ dimension; and ε_i is the random perturbation error term in $m \times 1$ dimension. The following assumptions are made on the set of equations: the mean of the errors is zero, i.e., $E(e_i) = 0$; each regression equation has an equal variance in the error terms and an unequal variance in the error terms across regression models, i.e., $\mathrm{var}(e_1) = \sigma_1, \mathrm{var}(e_2) = \sigma_2, , \mathrm{var}(e_m) = \sigma_m$. Furthermore, a relationship exists between the error terms of different models at an exact moment, i.e., $\mathrm{cov}(e_{jt}, e_{kt}) = \sigma_{jk}, j, k = 1, 2, , m, t = 1, 2, , n$; and the observed errors of different models at different moments are uncorrelated, i.e., $\mathrm{cov}(e_{jt_1}, e_{kt_2}) = 0, t_1 \neq t_2$. In this way, each equation is a classical regression equation, while these m classical linear regression models are linked together by the error assumptions. The above description can be succinctly expressed in the following matrix form:

$$\begin{cases} y = x\beta + e \\ E(e) = 0 \\ \mathrm{cov}(ee') = \sum \otimes I_m \end{cases} \tag{8}$$

where $y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{pmatrix}, x = \begin{pmatrix} x_1 & & & 0 \\ & x_2 & & \\ & & \ddots & \\ 0 & & & x_m \end{pmatrix}, \beta = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_m \end{pmatrix}, e = \begin{pmatrix} e_1 \\ e_2 \\ \vdots \\ e_m \end{pmatrix},$ and $\sum = \sigma_{ij}$ are positive symmetric matrices; I_m is the unit

Table 1 Indicators of economic-social impacts of carbon emission reduction in the construction sector

Stage	Impact indicator	Symbol	Bibliography	Categorization
Materialization phase	The gross output value of the construction industry (billion RMB yuan)	GOVC	(Onat et al. 2014; Zhang et al. 2021)	Economy
	The profit rate of output value (%)	PROV	(Braulio-Gonzalo et al. 2022)	Economy
	Construction industry research and experimental development funds (million RMB yuan)	CRE	(Zheng et al. 2019)	Society
	Price index of building materials and hardware (2010 as the base year = 100)	PIBH	(Gencturk et al. 2016; Kamali et al. 2018)	Economy
	The total turnover of primary building materials (million tons/km)	TTB	(Khan et al. 2018; Zheng et al. 2019)	Economy
	The average wage of construction workers (thousand RMB yuan)	AWC	(Huo et al. 2021; Tokede et al. 2021)	Society
	The average number of persons engaged in construction activities (many persons)	ANPC	(Capitano et al. 2011)	Society
	Energy consumption per unit construction area (kg standard coal/m^2)	ECPA	(Dobravec et al. 2021; Lazar and Chithra 2021)	Economy
Operation phase	The proportion of households with a green landscape in the community (%)	PHG	(Carvalho et al. 2019; TF Huo et al. 2020a, b)	Society
	Operation and maintenance price index (2010 as the base year = 100)	OMPI	(Lazar and Chithra 2021; Hasheminasab et al. 2022)	Economy

matrix of m × m; and ⊗ is the Kroneker product of the matrices.

Based on the above demonstration, the economic and social impacts were analyzed. In order to reduce the fluctuation of the variables and the degree of heteroskedasticity. C_{pro}, C_{trans}, C_{cons}, and CEO were logarithmically treated as independent variables, and the ten economic and social impact indicators were logarithmically treated as dependent variables. Considering that dependent variables may be jointly influenced by similar characteristics, similar unobserved factors, or missing information across the construction industry's life cycle (Washington et al. 2020), the following set of SUR equations is established:

The subscripts of the variables in the equations t indicate the corresponding values of the variables in the year t. Note that in the first eight equations above, the independent variables only include lnC_{pro_t}, lnC_{trans_t}, and lnC_{cons_t}. Because the first eight dependent variables correspond to the social and economic impacts in the materialization stage, the independent variable $lnCEO_t$ is added in the last two equations. In addition, because the last two dependent variables correspond to the social and economic impacts in the operation phase, and the materialization and operation phases are two closely related phases, the independent variables are chosen from the four equations above. To further prove the applicability of the SUR model from a quantitative perspective, the results of the SUR model

$$\begin{cases} lnGOVC_t = \alpha_G + \beta_{G1}lnC_{pro_t} + \beta_{G2}lnC_{trans_t} + \beta_{G3}lnC_{cons_t} + \varepsilon_{1t} \\ lnPROV_t = \alpha_{PR} + \beta_{PR1}lnC_{pro_t} + \beta_{PR2}lnC_{trans_t} + \beta_{PR3}lnC_{cons_t} + \varepsilon_{2t} \\ lnCRE_t = \alpha_C + \beta_{C1}lnC_{pro_t} + \beta_{C2}lnC_{trans_t} + \beta_{C3}lnC_{cons_t} + \varepsilon_{3t} \\ lnPIBH_t = \alpha_{PI} + \beta_{PI1}lnC_{pro_t} + \beta_{PI2}lnC_{trans_t} + \beta_{PI3}lnC_{cons_t} + \varepsilon_{4t} \\ lnTTB_t = \alpha_T + \beta_{T1}lnC_{pro_t} + \beta_{T2}lnC_{trans_t} + \beta_{T3}lnC_{cons_t} + \varepsilon_{5t} \\ lnAWC_t = \alpha_{AW} + \beta_{AW1}lnC_{pro_t} + \beta_{AW2}lnC_{trans_t} + \beta_{AW3}lnC_{cons_t} + \varepsilon_{6t} \\ lnANPC_t = \alpha_{AN} + \beta_{AN1}lnC_{pro_t} + \beta_{AN2}lnC_{trans_t} + \beta_{AN3}lnC_{cons_t} + \varepsilon_{7t} \\ lnECPA_t = \alpha_E + \beta_{E1}lnC_{pro_t} + \beta_{E2}lnC_{trans_t} + \beta_{E3}lnC_{cons_t} + \varepsilon_{8t} \\ lnPHG_t = \alpha_{PH} + \beta_{PH1}lnC_{pro_t} + \beta_{PH2}lnC_{trans_t} + \beta_{PH3}lnC_{cons_t} + \beta_{PH4}lnCEO_t + \varepsilon_{9t} \\ lnOMPI_t = \alpha_O + \beta_{O1}lnC_{pro_t} + \beta_{O2}lnC_{trans_t} + \beta_{O3}lnC_{cons_t} + \beta_{O4}lnCEO_t + \varepsilon_{10t} \end{cases} \tag{9}$$

are compared with those of the OLS model, which only responds to the regression relationship between variables. The differences in the results of the two models are analyzed to determine whether correlations exist between the equations and between the error terms of the equations. If so, the SUR model shall be more appropriate. Then, the internal relationships that exist can be identified.

Model fit effect and significance test

The coefficient of determination R^2, i.e., the root mean squared error (RMSE), was selected to test the model's fit, so as to determine whether the established equation can accurately describe the practice correlation between the dependent and independent variables. R^2 characterizes the extent to which the variation in the dependent variable y can be explained by the control independent variable x. $R^2 = 1 - \sum_{i=1}^{m}\left(y_i - \hat{y}_i\right)^2 / \sum_{k=1}^{m}\left(y_i - \overline{y_i}\right)^2$, where $y_i, i = 1, 2, \cdots, m$, is the observed value, $\hat{y}_i$ is the predicted value, and $\overline{y_i}$ is the mean value. When R^2 is closer to 1, it indicates a better fit of the equation. RMSE measures the deviation of the estimated value from the actual value, and its expression is $\sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(y_i - \hat{y}_i\right)^2}$: the closer to 0 the value, the better the

fit. In addition, a confidence interval of 95% or more was selected to test the significance of the estimated parameters of the model (Ganamé et al. 2021).

Data sources

The whole life cycle statistics of the construction industry in Shandong from 2010 to 2020 and the corresponding carbon emission factors were selected to calculate the total carbon emissions. The statistics were obtained from the statistical yearbooks published by different official agencies of China. Carbon emission factors for building materials and fuels were converted and summarized in reference to the IPCC for National Greenhouse Gas Inventory Guidelines (IPCC 2006), China's Provincial Greenhouse Gas Inventory Guidelines (National Development and Reform Commission 2011), and relevant literature (Yeo et al. 2016; Zhang and Wang 2017; Shan et al. 2018), as shown in Table 2. For electricity emission factors, the information on regional grids released annually by the Chinese Ministry of Ecology and Environment was referred to for baseline emission factors, as presented in Table 3.

The impact indicators were obtained from the Shandong Province Statistical Yearbook (Shandong Provincial Bureau of Statistics 2021), the China Statistical

Table 2 Carbon emission factors for building materials and related fuels

Material or fuel	Carbon emission factor	Unit
Steel	1.83	tCO_{2e} /t
Clinker	0.61	tCO_{2e} /t
Aluminum	7.47	tCO_{2e} /t
Timber	0.27	tCO_{2e} /m^3
Glass	0.07	tCO_{2e} /weight case (one weight case equals 50 kg)
Raw coal	1.98	tCO_{2e} /t
Cleaned coal	2.05	tCO_{2e} /t
Coke oven gas	0.834	$kgCO_{2e}$ /m^3
Liquefied petroleum gas	2.87	tCO_{2e} /t
Gasoline	3.11	tCO_{2e} /t
Diesel oil	3.15	tCO_{2e} /t
Natural gas	1.93	$kgCO_{2e}$ /m^3

Adopt the recovery rates of 10% and 30% for steel and aluminum, respectively

Yearbook (National Bureau of Statistics 2021c), and the China Statistical Yearbook of the Construction Industry (National Bureau of Statistics 2021b), with certain conversions conducted. In addition, the missing data were supplemented by interpolation with the available data. A descriptive statistical analysis of the obtained variable data is presented in Table 4.

Results and analyses

Analysis of the whole life cycle carbon emissions of the construction industry in Shandong Province

The carbon emissions and the carbon emission intensity (CEI) of the construction industry in Shandong from 2010 to 2020 were derived. CEI indicates the amount of carbon dioxide emitted per unit of GNP growth. Detailed data are given in Table 5, in combination with Fig. 2. Carbon emissions had generally shown an increasing trend since 2010; but they began to decrease in 2016, and reached the maximum of 309.156 million tCO_{2e} in 2019. The carbon emissions in the material production stage took the largest share, while those in the demolition stage were the smallest; this result with the findings in certain existing research (Zhang and Wang 2016b). It should be noted that the demolition stage will intensively generate construction waste. The carbon emissions generated in different building types, demolition methods, and transportation distances can vary significantly. While demolition emission may be insignificant in some cases, they may be significant in other cases, so they cannot be generalized. Although this study has analyzed the carbon emissions in the demolition stage in the whole life cycle of the construction industry in Shandong Province from a macroscopic perspective, the microscopic analysis should be made specific to the identified buildings.

The proportion of carbon emissions in the materialization phase reached the highest in 2015; then, it decreased. In the meantime, the proportion of carbon emissions in

Table 3 Baseline emission factors for the grids in Northern China, 2010–2020 (tCO_2 /MWh)

| Grid Name	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
East China Power Grid	0.991	0.980	1.002	1.030	1.058	1.042	1.00	0.968	0.946	0.942	0.932

Shandong Province is part of Northern China region

Table 4 Statistical description of the variables

Explained variables	Mean	Std. Dev	Min	Max
GOVC (billions RMB yuan)	1019.096	322.664	549.659	1494.730
PROV (%)	4.0545	0.763	2.600	4.900
CRE (million RMB yuan)	3266.478	1833.081	1384.600	6914.01
PIBH (2010 as the base year = 100)	106.978	3.952	100.000	113.280
TTB (million tons/km)	83,211.800	7938.866	75,297.950	100,925.700
AWC (thousand RMB yuan)	47.977	14.935	25.807	72.969
ANPC (many persons)	3223.182	252.063	2702.600	3518.400
ECPA (kg standard coal/m^2)	5.948	0.471	5.367	6.938
PHG (%)	54.664	9.872	41.470	68.400
OMPI (2010 as the base year = 100)	118.166	9.873	100.000	132.106

Table 5 Carbon emissions of the construction sector in Shandong by phase from 2010 to 2020 (million t CO_{2e})

Year	C_{pro}	C_{trans}	C_{cons}	CEO	C_{dcons}	C_{dtrans}	C	CEI
2010	103.744	13.320	7.845	55.457	0.776	0.525	181.677	0.331
2011	107.460	12.713	8.475	58.846	0.838	0.534	188.866	0.291
2012	118.226	15.914	8.702	64.433	0.861	0.592	208.728	0.287
2013	128.991	17.899	9.484	66.231	0.938	0.650	224.193	0.265
2014	135.934	18.264	9.939	78.897	0.983	0.682	244.699	0.263
2015	164.983	20.958	10.504	82.710	1.039	0.715	280.908	0.300
2016	125.165	15.924	10.766	100.156	1.065	0.628	253.704	0.252
2017	128.965	15.382	10.847	103.234	1.073	0.629	260.129	0.227
2018	137.925	15.961	11.031	110.782	1.091	0.663	277.453	0.215
2019	159.961	18.333	12.143	116.759	1.201	0.759	309.156	0.217
2020	142.421	14.823	12.628	123.048	1.249	0.648	294.816	0.197

CEI unit is: kg CO_{2e} /RMB

Fig. 2 Life cycle carbon emissions and the carbon emission intensity of the construction industry in Shandong, 2010 to 2020
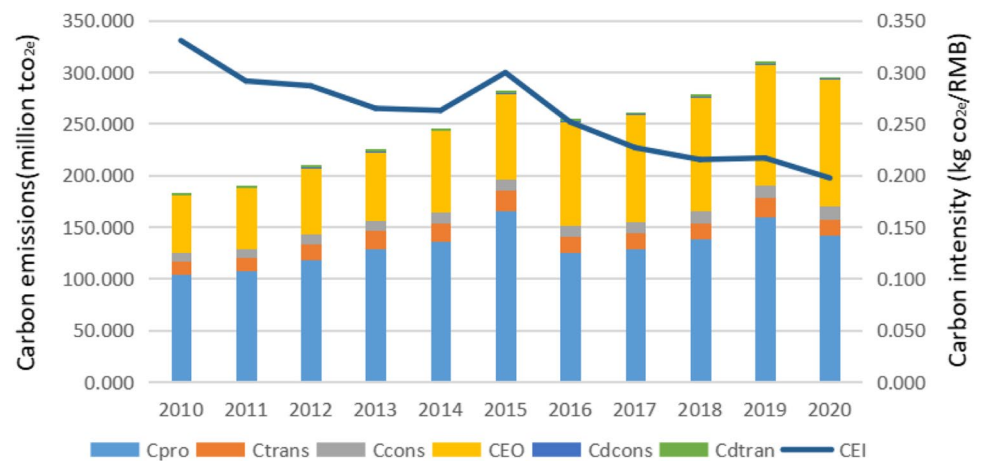
the operation phase increased. This phenomenon was related to the development policies in Shandong Province in recent years: such policies as the adoption of assembly construction technology, green materials, and energy conservation were proposed for the materialization phase (Liu et al. 2022). In addition, the per-capita economic standard of living has improved. As a result, the requirement for comfort in life has been boosted, leading to more energy consumption and carbon emissions in the operation phase. Especially, carbon emissions in the material production phase have become the main contributor, accounting for more than 80% of the emissions; thus, carbon emissions in the transportation and on-site construction phases have become close. It is important to note that the energy consumption in the transport phase is calculated based on the total transport turnover of the entire construction industry (including civil engineering and equipment installation), so it may be overestimated. However, this potential overestimation is acceptable, because it shows a decreasing trend in terms of CEI. The CEI in the construction industry was

reduced by 40.48% in 2020 from the level in 2010. In fact, the commitment made by the Chinese government in 2009 for the construction industry has been delivered.

Tests of data stationarity and cointegration

All the data adopted in this study are time series data, which should be checked for unit roots before analysis. Moreover, ADF (Maddala and Wu 1999) is a commonly used method for unit root test. The trend of the data can be observed from the scatter plot of each variable in Fig. 3. In this study, the ADF test is implemented to determine whether there is a unit root in the data, based on an original hypothesis that there is a unit root in the data as well as an alternative hypothesis that the data are smooth. As seen in Table 6, only two variables, i.e., ln*CRE* and ln*OMPI*, pass the test at the 1% significance level, and the variable ln*PROV* passes the test at the 5% significance level; the rest of the data are non-stationary. The variables are first order differenced, and all the data are smooth at the 5% significance level. Subsequently, a
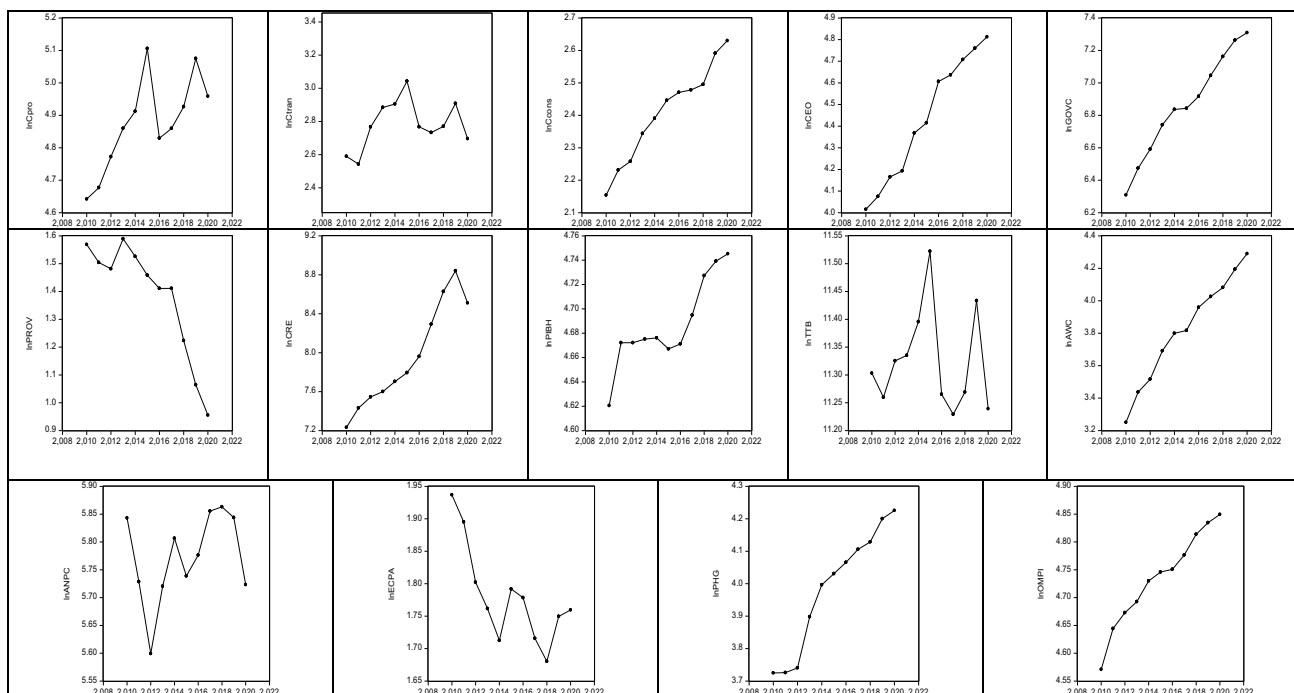
Fig. 3 Scatter plot of variables

cointegration test was conducted to determine whether there is a smooth long-run relationship between the variables. For this test, the Kao residual cointegration test method (Kao 1999) is commonly used. In this method, the null hypothesis

is that there is no cointegration relationship. And it uses the residuals from the regression of static data to construct the statistic. Table 7 demonstrates that the variables are all cointegrated at the 1% significance level, so the null hypothesis is rejected. Therefore, the independent variables of every single equation in the SUR equation set have a long-run cointegration relationship with the dependent variable.

Analysis of the SUR model

Combined with Eq. (9), the economic and social impact of CECI in Shandong Province was analyzed. It can be seen from Table 8, SUR and OLS model fit and significance test comparison, only the fit effect and significance test of the ln$ANPC$ equation fails, indicating that CECI does not significantly affect the total number of employees. Therefore, the equation is removed from the SUR equation set. However, the rest of the equations pass the OLS and SUR model fit and significance tests. The RMSE figures, except for the Ln$ANPC$ equation, are ranged from 0.014 to 0.189, and the R^2 values are ranged from 0.7098 to 0.9904; so all of them pass the test at the 1% significance level, indicating that the SUR model developed in this study can accurately express the relationship between the dependent and independent variables.

As seen from the results of the SUR simulation in Table 9, the behavior of lnC_{cons} affects ln$GOVC$ positively and significantly: Increase in C_{cons} may be a hike in construction volume,

Table 6 ADF unit root test for variables

Variable	Level	First difference
Independent variable		
lnC_{pro}	-2.0786	-3.5155^{***}
lnC_{tran}	-2.1243	-3.0449^{***}
lnC_{cons}	-2.1983	-3.3198^{**}
lnCEO	-2.2148	-5.0305^{***}
Implicit variable		
ln$GOVC$	-2.8704	-4.3851^{**}
ln$PROV$	-2.1186^{**}	-5.6757^{**}
lnCRE	-5.6037^{***}	-1.9287^{**}
ln$PIBH$	-2.0735	-3.4808^{***}
lnTTB	-2.7051	-3.5692^{***}
lnAWC	-3.0712	-4.3159^{**}
ln$ANPC$	-3.5427^{*}	-4.4007^{***}
ln$ECPA$	-2.5822	-2.3901^{**}
lnPHG	-1.9899	-5.6744^{**}
ln$OMPI$	-5.2919^{***}	-4.5029^{***}

***, **, and * denote significance levels at $p \leq 1\%$, $p \leq 5\%$, and $p \leq 10\%$, respectively, which are all statistically significant. It is the same for the subsequent tables

Table 7 Cointegration test for the unit root of Kao residual term

	r-ln$GOVC$	r-ln$PROV$	r-lnCRE	r-ln$PIBH$	r-lnTTB	r-lnAWC	r-ln$ANPC$	r-ln$ECPA$	r-lnPHG	r-ln$OMPI$
ADF-t	− 3.1081***	− 3.1086***	− 3.5911***	− 4.5318***	− 3.6859***	− 4.4157***	− 3.3736***	− 4.5430***	− 4.9893***	− 3.1589***

and increases in construction volume will in turn lead to a boost in *GOVC*. As a pillar industry in China, the construction sector has contributed much to the rapid growth of its GDP and carbon emissions (He et al. 2020). ln*PROV* has a negative relationship both with lnC_{pro} and lnC_{cons}, indicating that the lower the carbon emissions from the materials and the greener the construction, the higher the *PROV*. However, ln*PROV* has a positive correlation effect with lnC_{trans}. ln*CRE* are heavily influenced by lnC_{cons}, which is related to the relevant policies for China's construction industry. The China government has encouraged the construction industry to implement green construction methods and enhance research on "carbon neutral" and "carbon peaking" (MOST 2022). ln*PIBH* is also positively related to the behavior of lnC_{cons}, which can be interpreted by the fact that an increase in C_{cons} would lead to an increase in the construction volume. Such increase will inevitably require more building materials; thus, *PIBH* will increase accordingly, but the impact is insignificant. ln*TTB* is positively related to lnC_{pro}, mainly because *TTB* will increase in C_{pro} as more materials are required and more carbon emissions are emitted. However, it is negatively correlated with lnC_{cons}, probably because housing buildings require a high percentage of assembled blocks (HURCDSD 2022). ln*AWC* is more positively influenced by lnC_{cons}, indicating that as C_{cons} is increased and more work is done, more wages would be paid to workers. ln*ECPA* is mainly related to lnC_{cons} in a negative correlation, which may still be associated with the assembly construction technology. ln*PHG* showcases a positive relationship with both lnC_{cons} and ln*CEO*. When residents want to improve the health and comfort in their lives, they will need a larger floor area and more domestic energy consumption. This result is consistent with the findings of T Huo et al. (2020a, b). Similarly, ln*OMPI* positively correlates with both lnC_{cons} and ln*CEO*.

By comparing with the OLS model results, it is found that the coefficients and significance obtained from the two analysis methods for the ln*GOVC* and ln*TTB* equations are consistent, indicating no correlation exists between the error terms of these two equations and the rest of the equations. The OLS and SUR analysis also shows that for ln*PHG* and ln*OMPI*, the coefficients and significance of the two equations are entirely different, indicating that the error terms of ln*PHG* and ln*OMPI* equations and the rest of the equations are interdependent. Although consistent coefficients were obtained for the remaining equations in the analysis of OLS and SUR models, there were some significant differences. Overall, the SUR model analysis finds that the efficient coefficients are better than the results in OLS model analysis.

Discussion

Shandong, a coastal province in Eastern China, governs 16 prefecture-level cities, with a resident population of more than 101 million by the end of 2022 (Shandong Provincial

Table 8 SUR vs. OLS model fit and significance test

Equation	Parms	SUR			OLS		
		RMSE	R-sq	p	RMSE	R-sq	p
ln$GOVC$	3	0.0609	0.9629	0.0000	0.0764	0.9629	0.0000
ln$PROV$	3	0.0676	0.8855	0.0000	0.0847	0.8855	0.0011
lnCRE	3	0.1884	0.8624	0.0000	0.2362	0.8624	0.0021
ln$PIBH$	3	0.0155	0.8061	0.0000	0.0194	0.8061	0.0069
lnTTB	3	0.0256	0.9141	0.0000	0.0320	0.9141	0.0004
lnAWC	3	0.0306	0.9904	0.0000	0.0383	0.9904	0.0000
ln$ANPC$	3	0.0726	0.1019	0.7414	0.0910	0.1019	0.8488
ln$ECPA$	3	0.0394	0.7098	0.0000	0.0494	0.7098	0.0269
lnPHG	4	0.0288	0.9740	0.0000	0.0379	0.9754	0.0001
ln$OMPI$	4	0.0144	0.9686	0.0000	0.0193	0.9690	0.0001

Table 9 Comparison of SUR and OLS models' estimation results

Explanatory variables	ln$GOVC$	ln$PROV$	lnCRE	ln$PIBH$	lnTTB	lnAWC	lnECPA	lnPHG	ln$OMPI$
SUR									
lnC_{pro}-coef		−1.520*** (0.567)			0.976*** (0.215)	−0.551** (0.257)	0.633* (0.331)		
lnC_{trans}-coef		1.448** (0.370)					−0.531** (0.216)		
lnC_{cons}-coef	2.507*** (0.309)	−0.580* (0.343)	2.789*** (0.955)	0.162** (0.078)	−0.736*** (0.130)	2.518*** (0.155)	−0.650*** (0.200)	0.809*** (0.207)	0.393*** (0.088)
lnCEO-coef								0.223*** (0.069)	0.065*** (0.023)
Alpha -coef	2.909*** (1.077)	6.157*** (1.194)		3.992*** (0.273)	8.272*** (0.451)		1.735** (0.696)	1.012** (0.500)	3.269*** (0.253)
OLS									
lnC_{pro}-coef		−1.520* (0.711)			0.976*** (0.269)	−0.551 (0.322)	0.633 (0.415)		
lnC_{trans} -coef		1.448** (0.464)					−0.531* (0.271)		
lnC_{cons} -coef	2.507*** (0.387)	−0.580 (0.429)	2.789* (1.198)	0.162 (0.098)	−0.736*** (0.162)	2.518*** (0.194)	−0.650** (0.250)	0.553 (0.483)	0.326 (0.246)
lnCEO-coef								0.340 (0.203)	0.095 (0.359)
Alpha-coef	2.909*** (1.349)	6.157*** (1.194)		3.992*** (0.342)	8.272*** (0.566)		1.735* (0.696)	0.883 (0.706)	3.235*** (0.359)

Bureau of Statistics 2022). In this province, the construction industry is also a pillar for its national economy, so the government has attached importance to the development of this industry. During its 14th Five-Year Plan period, Shandong Province would be focused on promoting the development of ultra-low-energy and low-carbon buildings on a large scale, so as to ensure that it would achieve the carbon peak by 2030 (Shandong Provincial People's Government 2022).

As shown in the "Analysis of the whole life cycle carbon emissions of the construction industry in Shandong Province" section, carbon emissions in Shandong Province were in an upward trend from 2010 to 2020. This increase is related to the urbanization process across the province

(Zhang et al. 2021). As a developed province in China, Shandong needs to construct many housing buildings to meet the demand of economic development in the urbanization process (Ahmad et al. 2019). However, the CEI is in a decreasing trend, which indicates that the construction industry in Shandong is gradually following the low carbon emission practice.

The key to achieving green and low-carbon development by the construction industry in Shandong Province is to identify the critical points and main factors that may influence carbon emission, while understanding the socioeconomic impact in the process of implementing carbon emission reducing measures. The existing research has found

that the operation phase is the most carbon-emitting period, while the materialization phase is the most CEI-prone period (Zhang and Wang 2017; Jayawardana et al. 2021). In addition, carbon emissions can be reduced by improving energy efficiency, promoting green building materials, and implementing low-carbon designs (DZ Li et al. 2020a, b; Zhang et al. 2021). However, no systematic exploration has been made on the economic and social impacts of low carbon emissions in the construction industry. This study identifies the main factors of carbon emissions that may impact society and economy by using the process-based carbon emission calculating method based on data from the UN Sustainable Development Goals and China's 14th Five-Year Plan. This is an innovative practice of this study. To reveal the correlation between carbon emissions and the impact factors on society and the economy in each stage, the SUR model was used. The SUR model is found more suitable than the OLS model for this study. The innovation of this study can be illustrated in the following two aspects.

By implementing a low-carbon emission reduction project for Shandong Province's construction industry, this study has found that three factors, i.e., *GOVC*, *CRE*, and *PIBH*, show a significant positive relationship with C_{cons}. There is a positive correlation between market factors and carbon emissions (Du et al. 2021). *PROV* is significantly related to all the three sub-processes of the materialization phase. Implementing environment-friendly materials and green construction methods will increase *PROV* accordingly (Huo et al. 2021). *TTB* shows a positive relationship with C_{pro} and a negative relationship with C_{cons}, while *AWC* shows an opposite relationship with these two phases. In combination with the corresponding elasticity coefficients, an increase in C_{pro} would promote an increase in *TTB*; and although it shows a negative correlation with *AWC*, the effect is not significant. C_{cons} and *AWC* will increase when *TTB* decreases; this may be associated with the optimal management of construction sites and the progress in construction technology. The effective combination of capital and labor and the hiking construction efficiencies in enterprises can be used as a strategy to control emissions (Pui and Othman 2019). There is a significant relationship between *ECPA* and carbon emissions in all the three sub-processes of the materialization stage, and there is a negative relationship mainly with C_{cons}, indicating that the construction industry in Shandong Province is continuously adopting green construction methods (HURCDSD 2022). The factors of *PHG* and *OMPI* positively correlate with C_{cons} and *CEO*, and the error terms of the equations corresponding to these two factors show a certain degree of dependence on other equations.

In general, a certain cross-influence is found between the dependent variables. So it is not reasonable to simply hope reducing or increasing the carbon emissions in a certain sub-stage; instead, it is necessary to analyze specific circumstances for specific problems. For example, in the developed cities in China, the implementation of assembled blocks in the construction phase can contribute to the sustainable development of social indicators, but the profitability of the relevant enterprises would be lowered (Zhou et al. 2022). The results of this study provide some theoretical and empirical support for the government's functional departments in macro-regulation. And this study's research methodology is also applicable to similar explorations in other regions.

Conclusions and policy implications

This study analyzed the social and economic impacts of CECI at the provincial level. By taking Shandong Province as an example, it calculated the carbon emissions in the construction industry from 2010 to 2020 in a life cycle carbon emission calculating method based on the process analysis method. The impact of carbon emissions on the economy and society in each stage was deeply explored. With literature review and expert interviews, six economic and four social impact factors were identified. After tested for smoothness and cointegration, the data were analyzed to find out the influencing factors by using the SUR model. The following conclusions were obtained:

(1) The carbon emissions in the construction industry in Shandong showed an overall increasing trend from 2010 to 2020, with a slight decrease in 2016, and reached a maximum of 309.156 million t CO_{2e} in 2019, followed by a decrease in 2020. The material production and operation stages were the main contributors of carbon emissions, so they should be the primary control stages for carbon emission reduction. In addition, the analysis of CEI shows a decreasing trend, indicating that the construction industry in Shandong Province was implementing low carbon measures year by year.

(2) The results of the SUR model analysis show that C_{pro} has a significant negative relationship with *PROV* and *AWC*, but has a significant positive relationship with *TTB* and *ECPA*. C_{trans} showcases a positive correlation with *PROV* and a significantly negative correlation with *ECPA*. C_{cons} has a significant relationship with all the ten dependent variables, except for *PROV*, *TTB*, and *ECPA*, which have significant negative correlations, and all other factors significantly positive correlate. The construction phase shall be the main control phase for macro-regulation. *CEO* has a significant positive correlation, mainly with *PHG* and *OMPI*. On the other hand, *ANPC* has no significant effect relationship with carbon emissions in all stages.

(3) A comparative analysis of the SUR and OLS models' results demonstrates that the error terms of the $\ln GOVC$ and $\ln TTB$ equations have some degree of interaction with the remaining equations' error terms, especially for $\ln PHG$ and $\ln OMPI$ equations; however, $\ln GOVC$ and $\ln TTB$ equations exhibit independence. The SUR model can yield better coefficients than the OLS model.

In the life cycle process of the construction industry, C_{pro} and *CEO* account for more than 85% of carbon emissions, so it should be the primary control stage for carbon emission reduction. Firstly, the waste of main building materials, such as steel, cement, and glass, should be reduced in the material production stage. And the production shall be conducted in a high-efficiency manner, and energy-saving should be strengthened. In addition, it is necessary to choose low-carbon raw materials or few-waste-producing building materials, while enhancing the support for research and development of green building materials. Secondly, carbon emissions in the operation stage come mainly from the use of energy, so the energy structure should be optimized by using new energy, while the promotion and subsidization of energy-efficient home appliances should also be strengthened. In the design of buildings, local climates should be considered, so as to make full use of natural resources to save energy and cut emissions. Finally, carbon emissions in the transportation, on-site construction, and demolition phases are relatively small, but they should not be ignored. The use of local building materials shall be encouraged to reduce the consumption of transportation-requiring materials and related energy. Moreover, it is necessary to boost the application of assembled buildings, optimize the organization design of construction, and adopt new technologies and techniques in the construction process.

Implementing low carbon emission in the construction stage would have an important effect on the economy and society. In order to promote the development of green buildings and scientific management by construction enterprises, government departments can start from the construction stage by formulating relevant incentive policies, such as financial support, tax relief, and other measures. To a certain extent, it can promote the stable growth of *GOVC* and *PIBH*, etc. These practices can also facilitate a virtuous cycle of economy and society. The economic and social impacts of carbon emissions in the material production, transportation, operation, and demolition stages, although relatively small, should also be carefully coped with. Government agencies should make coordination with related enterprises, such as building material manufacturers and transportation firms, to seek sustainable development and advocate environmental awareness among the general population. This can be implemented through formulating environmental laws and regulations and related policies. In addition, construction enterprises, building material manufacturers, and transportation firms should pay attention to green management and make green innovation one of their important strategies in production.

Although this study provides a new direction for the sustainable development of the construction industry by analyzing the economic and social impacts of the whole life cycle carbon emissions of the industry, it has certain shortcomings. First, in selecting economic and social impact indicators, although relatively extensive analysis and screening were implemented, the indicators finally chosen may not be complete. Future research should look for other possible impact indicators beyond this study. Second, expert interviews were conducted only with Chinese construction and related industry practitioners and relevant experts, thus somehow limiting the scope of the research. Future research shall expand the research subjects and horizons, especially making comparative analyses between different industries or countries, so as to enhance the generalizability of the results.

Appendix

Table 10 Expert information sheet

Number	Unit Type	Position/title	Experience (years)
1	Research institutions in universities	Professor	25
2	Research institutions in universities	Professor	28
3	Government Agencies	Department Head	15
4	Developers	General Manager	20
5	Developers	Manager	10
6	Construction companies	Senior Engineer	17
7	Design Institute	Chief Engineer	13
8	Suppliers	Regional General Manager	12

Data availability The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethical approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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