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Carbon Emission Control and Environmental Optimization of Industrial Heritage Clusters Combined with Eco-Architectural Concepts in Housing Development

Yin Cheng[1,*]
[1] College of Art, Zhejiang Shuren University, Hangzhou, Zhejiang, 310015, China
Corresponding authors: (e-mail: chengyin05715722@163.com).

Abstract The upgrading of the urbanization stage has made industrial heritage and low-carbon housing development one of the core concerns of sustainable urban development. This paper is based on the concept of eco-architecture, and chooses the carbon emission model of the construction industry to measure carbon emissions, and other data. And the Extreme Boundary Analysis (EBA) model and panel data model are used as the empirical analysis methods for the relationship between multiple variables and carbon emissions. Taking Province I as the research sample, the carbon emissions and related data of the construction industry in Province I from 2010 to 2019 are calculated as the research data. Meanwhile, for the strategy research of carbon emission control, focusing on the carbon emission influencing factors, nine target variables including energy structure, energy efficiency, and local financial final expenditures are selected from energy factors and economic factors. The EBA model is used to test the combination of variables, in which the combination of energy efficiency, energy consumption structure, and energy price is the main variable with $P(\beta)$=0.0000, showing a "strongly significant" relationship. Therefore, the carbon emission control strategy in housing development should focus on the optimization of energy selection and structure.

Index Terms carbon emission in construction, limiting boundary analysis model, panel data model, eco-building, industrial heritage

I. Introduction

Nowadays, low carbon and sustainability have become the main development goals of countries around the world. At the same time, a series of issues such as caring for the environment and saving resources have become popular symbiotic topics nowadays. Cities are not only places where people live, work and relax, but also major sources of carbon emissions [1]. Although, urban areas cover only 2.4% of the global land area, they contribute about 80% of the global carbon emissions as the key areas carrying the development of major national strategies [2]. With the acceleration of economic development and urbanization, the energy consumption and carbon emissions of the building sector are getting higher and higher, becoming one of the important contributing sources of global climate change and environmental pollution problems [3]-[5]. Therefore, strengthening building energy conservation and emission reduction has become a social responsibility and development requirement that the state and enterprises must have.

For a long time, there have been subjective, utilitarian and blind problems in the transformation and protection of industrial heritage, and the view of tearing down and rebuilding and demolishing to the end still exists. For some enterprises, the blind development, sale, and leasing brought about by the excessive pursuit of economic value, one-sidedly pursuing short-term interests and economic benefits, ignoring the resulting loss of urban memory caused by the disconnection of industrial culture and the destruction of industrial relics, as well as the frequent occurrence of pollution and waste, and the green, environmentally friendly, low-carbon, and sustainable aspects of some transformation projects are only in the feasibility report [6]-[10]. At the same time, the historical, social, technological, cultural and economic values of industrial heritage in the process of transformation and transformation of industrial heritage should be developed and reused, and it should be truly recognized that the protection of industrial heritage is a respect for historical integrity and creativity of human society, a commemoration of the contribution of traditional industry, and the inheritance of its noble spirit, so as to truly realize the continuation of urban memory, realize the environmental protection and sustainable development of mankind, realize the memory and regeneration of culture, and realize the construction of national spirit and humanistic spirit [11]-[15].

Some studies have shown that the carbon emission and environmental pollution of industrial heritage demolition and reconstruction can be effectively improved with the application of eco-technology [16]. In today's society, with the increasingly severe environmental problems and the pursuit of sustainable development, eco-architecture, as an innovative architectural concept and practice, is gradually receiving widespread attention. If we start from the concept of eco-building system design in the field of construction, and comply with high energy efficiency, resource conservation, environmental friendliness, high environmental quality, flexibility, adaptability, etc., we can avoid a large number of remodeling of our own construction projects later, reduce the consumption of limited resources, control carbon emissions, and improve the environment [17]-[20].

This paper explains the basic concepts and formulas of the direct carbon emission model, indirect carbon emission model and carbon emission intensity model, which constitute the carbon emission model of the construction industry as a measurement method of carbon emission and related factors. Then the limiting boundary analysis model and panel data model are introduced to assist in analyzing the statistical relationship between the target variables and carbon emissions, and the estimation and testing process of the limiting boundary analysis model is highlighted. Subsequently, the building carbon emission data of Province I from 2010 to 2019 is used as the research sample to determine the target variables, and the Hausman test and basic test are carried out. Finally, different combinations of variables are constructed and analyzed using the EBA model. After synthesizing the analysis, the carbon emission control strategy of industrial heritage clusters in housing development is proposed.

II. Methodology for analyzing carbon emission control in housing development

II. A. Carbon Emission Modeling for the Construction Industry

In order to screen out the applicable methods for calculating carbon emissions in the construction industry, this paper summarizes and analyzes the currently used carbon emission methods, mainly the whole life cycle method, the actual measurement method, the material balance method, the carbon emission coefficient method and the input-output method.

Carbon emissions from the construction industry has always been an issue of continuous and in-depth research in the industry, and the carbon emission coefficient method is currently used in the construction industry, which is more accurate, simple in application, with less error, and has multiple cases for reference. Therefore, this paper applies the carbon emission coefficient method to measure the carbon emissions of the construction industry.

The method divides carbon emissions from the construction industry into two major parts, direct and indirect, in order to more accurately assess the impact of construction activities on the environment. Direct carbon emissions from the construction industry mainly come from carbon emissions brought about by the direct consumption of fossil energy and consumed electricity and heat during the operation phase of buildings. Indirect carbon emissions mainly refer to the carbon emissions generated during the production of building materials as shown in Figure 1.The carbon emission measurement model for the construction industry is shown in equation (1):

$$C = C_1 + C_2 \tag{1}$$

where C - is the total carbon emissions from the construction industry, C_1 - the direct carbon emissions from the construction industry, C_2 - indirect carbon emissions from the construction industry.

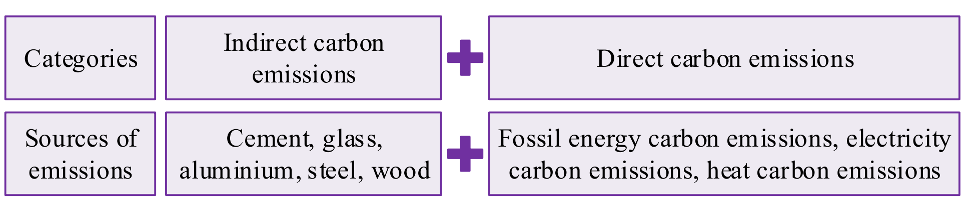

Figure 1: Carbon emission sources of construction industry

II. A. 1) Direct carbon emission modeling

According to the classification of fuels and previous studies, direct carbon emissions are mainly selected from 10 types of energy sources such as raw coal, coal type, coke, gasoline, diesel, liquefied petroleum gas (LPG), natural gas, other petroleum products, heat and electricity. The formula for calculating direct carbon emissions from the construction industry is shown in equation (2):

$$C_1 = \sum_{i=1}^{n} f_i \times t_i \times y_i \times q_i \times \frac{44}{12} + f_e \times \alpha + f_h \times \beta \tag{2}$$

where i - type of energy, f_i - consumption of the i th type of energy in the construction industry, in tons, t_i - average low level heat generation of the i th type of energy, unit: KJ/Kg, y_i - carbon content per unit calorific value of the i th energy source, in tC/TJ, q_i - carbon oxidation rate of the i th energy source, $44/12$ - the ratio of the relative molecular mass of carbon dioxide to carbon, f_e - electricity consumption in the building sector, in billion kWh, α - carbon emission factor for electricity, f_h - Thermal power consumption of the construction industry in millions of kilojoules, β - Carbon emission factor for heat.

II. A. 2) Indirect carbon emission modeling

With reference to relevant studies, in assessing indirect carbon emissions from the construction industry, this paper selects five major construction materials that are closely related to the construction industry: steel, wood, cement, glass and aluminum. Given the recyclable nature of steel and aluminum, the recycling process of these two materials is taken into account in order to more accurately calculate their actual consumption in the construction industry. The formula for calculating indirect carbon emissions from the construction industry is shown in equation (3):

$$C_2 = M_j \times r_j \times (1-\theta_j) \tag{3}$$

where M_j - the amount of the j th building material used, in KG, r_j - CO_2 emission coefficient of the j th building material, θ_j - the recycling coefficient of the j th building material.

II. A. 3) Carbon intensity modeling

Carbon intensity is an important indicator for measuring the level of regional carbon emissions. In view of the significant differences in the economic development status between regions, compared with the absolute amount of carbon dioxide emissions, it is more objective and comparable to use the indicator of carbon emission intensity to assess the carbon emission level of each region. The formula is shown in equation (4):

$$CI = C / GDP \tag{4}$$

where CI - carbon emission intensity, C - carbon dioxide emissions in tons, GDP - gross domestic product of the construction industry.

II. B.Limit boundary analysis model

The EBA model, or Extreme Boundary Analysis model, the robustness of the coefficients of this multiple linear regression model is tested as the set of conditioning variables is progressively changed, and the main function is to perform sensitivity analysis.

II. B. 1) EBA model estimation

EBA models are usually estimated in two steps:

In the first step, the explanatory variables relevant to the model are first divided into three categories, the target variable set (M), i.e., the set of variables of interest to the researcher. The core variable set (I), i.e., the set of explanatory variables that are directly related to the dependent variable. Conditional variable set (Z), i.e., the set of important explanatory variables that have an effect on the dependent variable, which is introduced to determine the possible range of values of the regression coefficients of the target variable. Among them, the core and conditional variable sets are mainly determined based on economic theories and existing relevant research results. After determining these three types of variables, the EBA model can be expressed as equation (5):

$$Y = \alpha + \beta_1 I + \beta M + \beta_2 Z + \mu \tag{5}$$

The regression equation of the dependent variable Y with the target variable M and the core set of variables I is first estimated as in equation (6):

$$Y = \alpha + \beta_1 I + \beta M + \mu \tag{6}$$

Call equation (6) the base regression. If the coefficient of the target variable β is statistically significant, continue to the second step. If it is not significant, possibly due to bias in the model setup or the target variable is not more significantly related to the explanatory variables themselves, then there is no need to continue.

In the second step, multiple traversal regression estimation of equation (5) is performed, i.e., regressing all possible linear combinations of all variables in the conditional variable set Z to find the maximum value $\beta_{\max}$ and the minimum value $\beta_{\min}$ of the target variable's regression coefficients β, if they are of the same sign and

β, $\beta_{\max}$ and $\beta_{\min}$ are statistically significant, the regression coefficients of the target variable are considered robust.

The EBA model is prone to multicollinearity, which makes the model standard error too large. If too many conditional variable set variables are introduced, it is also extremely labor intensive to traverse the regression for all possible linear combinations of them. Therefore, 3 restrictions are followed when selecting variables:

(1) For the core variable set I only 3 explanatory variables that are directly related to the dependent variable Y are generally selected.

(2) For the conditional variable set Z at least 3 to 7 potential explanatory variables that cannot be highly correlated with the target variable are selected.

(3) When performing an ergodic regression, there should not be more than 8 explanatory variables in principle.

II. B. 2) EBA model testing

The EBA model test is also divided into two steps: the first step is to calculate the upper and lower bounds of the limit. That is, equations (7)-(8):

$$\beta_u = \beta_{\max} + 2\delta_{\max} \tag{7}$$

$$\beta_d = \beta_{\min} - 2\delta_{\min} \tag{8}$$

where $\delta_{\max}$ and $\delta_{\min}$ are the standard deviations of the coefficients $\beta_{\max}$ and $\beta_{\min}$ respectively.

The second step is to formulate the original hypothesis that the relationship between the dependent variable and the target variable is “non-significant”, and the three conditions that must be met to reject the original hypothesis in the test are:

(1) $\beta \in [\beta_d, \beta_u]$.

(2) $0 \notin [\beta_d, \beta_u]$, i.e., the sign of the maximum and minimum boundaries must be the same.

(3) β, $\beta_{\max}$ and $\beta_{\min}$ must all be statistically significant in the regression model.

If any of these three conditions are not met, only the original hypothesis that the relationship between the dependent variable and the target variable is not significant is accepted. If all three conditions are met, the original hypothesis is rejected, i.e., the relationship between the dependent variable and the target variable is “strongly significant”.

II. C. Panel data model

The panel data itself contains three-dimensional information of cross-section, time and indicators, and the panel data model gathers the common characteristics of time series and cross-section data, which can reflect the pattern of each individual data at a certain point in time as well as describe the pattern of each individual change over time.

The basic form of the panel data model is equation (9):

$$y_{it} = \alpha_{it} + x'_{it}\beta_{it} + u_{it}, \quad i = 1,2,\cdots,N, \quad t = 1,2,\cdots,T \tag{9}$$

where y_{it} is the dependent variable, x_{it} is the vector of the $k \times 1$ dimensional independent variable, N is the number of individuals of the cross-section members, T is the number of observation periods for each cross-section member, α_{it} represents the constant term, β_{it} represents the $k \times 1$ dimensional coefficient vector corresponding to the independent variable vector x_{it}, k represents the number of explanatory variables, and u_{it} represents the random error term, and $u_{it} \sim iid(0, \sigma^2)$.

According to the different restriction requirements of the coefficient vector β and the intercept term vector α on each component, the model described in Eq. (9) is classified into three types: constant coefficient model without individual effects, variable intercept model, and variable coefficient model with individual effects. The corresponding single-equation regression forms are represented by Eqs. (10)-(12), respectively:

$$y_{it} = \alpha + x'_{it}\beta + u_{it}, \quad i = 1,2,\cdots,N, t = 1,2,\cdots,T \tag{10}$$

$$y_{it} = \alpha_i + x'_{it}\beta + u_{it}, \quad i = 1,2,\cdots,N, t = 1,2,\cdots,T \tag{11}$$

$$y_{it} = \alpha_i + x'_{it}\beta_i + u_{it}, \quad i = 1,2,\cdots,N, t = 1,2,\cdots,T \tag{12}$$

Before establishing Panel Data model, it is necessary to test which form the sample data conforms to in order to avoid errors in model setting, which is usually carried out with analysis of covariance.

Among them, the variable intercept model is subdivided into fixed impact variable intercept model and random impact variable intercept model, before determining whether it is a fixed impact or random impact, the random impact model is established on the data, and then the model is tested to see whether it meets the assumption that individual impacts are not correlated with the explanatory variables, and if it meets the assumption, the model is determined as a random impact model, and conversely, the model is determined as a fixed impact model. As to how to test whether the individual impact and explanatory variables in the model are correlated, in this regard, scholars have proposed a rigorous statistical test - Hausman test.

III. Analysis and Strategies for Controlling Carbon Emissions from Housing Development

III. A. Data sources and calculations

The energy consumption of transportation, transportation, warehousing and postal services, wholesale and retail, accommodation and catering, living and other energy from 2010 to 2019 was selected from the government energy statistical yearbook of that year. Table 1 shows the panel data of carbon emissions in the building operation stage of Province I from 2010 to 2019, in which "C1" is the carbon emissions of transportation, warehousing and postal services (tCO_2), "C2" is the carbon emissions of wholesale, retail, accommodation and catering (tCO_2), "C3" is other carbon emissions (tCO_2), "C4" is the carbon emissions of living (tCO_2), and "C5" is the carbon emissions of building operation (tCO_2).

Table 1: Carbon emissions during the operation stage of buildings

Year	C1	C2	C3	C4	C5
2010	23662940.46	13018198.71	174469150.5	108415194.44	174469150.52
2011	25984394.80	14447517.58	328292317.2	112624528.42	185265368.91
2012	26618591.57	16215584.54	332571078.3	119780944.85	197468294.63
2013	27257446.09	28632192.30	263164577.2	136550419.42	228469264.68
2014	26310132.32	36504161.09	383950311.3	150078667.35	263164577.15
2015	31325073.41	40891364.32	228469264.7	167603761.95	306439527.62
2016	34480229.71	42968257.34	306439527.6	184303732.48	332571078.34
2017	33696267.95	54902427.66	185265368.9	217768270.31	328292317.16
2018	36564010.43	51355914.34	197468294.6	214473407.93	383950311.32
2019	38524990.96	52284414.96	397287460.9	218620886.92	397287460.93

Table 2 further summarizes the total construction carbon emissions in Province I from 2010 to 2019, in which "A1" is the carbon emissions in the production stage of building materials (tCO_2), "A2" is the carbon emissions in the construction and demolition stages (tCO_2), "A3" is the carbon emissions in the building operation stage (tCO_2), and "A4" is the carbon emissions in the building operation stage (tCO_2). It can be seen that the carbon emissions of the construction industry in Province I are growing as a whole, and compared with 2010, the carbon emissions of (C5) building operation in 2019 have increased by about 18.73%.

Table 2: Summary of building carbon emissions

Year	A1	A2	A3	A4
2010	165073266.2	9665087.9	174469150.5	349207504.7
2011	154874439.7	9795687.49	328292317.2	492962444.4
2012	156174852.2	9524120.7	332571078.3	498270051.2
2013	238836650.9	8339269.1	263164577.2	510340497.1
2014	96698207.83	35998166.7	383950311.3	516646685.9
2015	280603013.6	8482065.39	228469264.7	517554343.6
2016	245610541.4	9086188.01	306439527.6	561136257
2017	546394734.8	11260128.24	185265368.9	742920232
2018	589114565.4	11607227.02	197468294.6	798190087
2019	565336802.8	35894867.11	397287460.9	998519130.9

The building carbon emissions and annual growth rate in Province I are shown in Figure 2. On the whole, the building carbon emissions in Province I have been increasing year by year, and despite the largest increase in

2011, when the annual growth rate exceeded 40%, its building carbon emissions only reached the peak of the decade in 2019, exceeding 1 billion tCO_2.

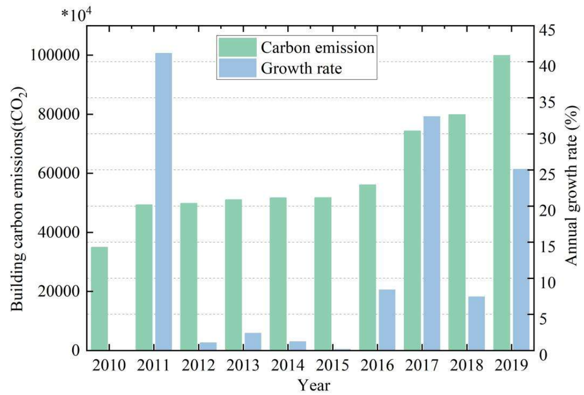

Figure 2: Carbon emissions and annual growth rate of buildings in Province I

III. B. Variable settings

In order to more accurately analyze the building carbon emissions at this stage, this paper combines the existing research with the actual situation, and selects nine target variables from five directions, namely, economic factors, industrial factors, energy factors, transportation factors and technological factors, as follows:

(1) Local fiscal final expenditure (*LFS*). On the one hand, the local fiscal expenditure for infrastructure construction will lead to a large amount of energy consumption, which will increase carbon emissions. On the other hand, expenditures for pollution prevention and environmental protection in local government fiscal expenditures are conducive to reducing carbon emissions.

(2) Trade Openness (*TO*). The total amount of imports and exports of each province expressed in RMB prices in the calendar year as a percentage of the province's Gross Regional Product (GRP).

(3) Foreign Direct Investment (*FDI*). The RMB price of the actual use of FDI.

(4) Level of urbanization (*CSH*). Large-scale infrastructure construction in the process of urbanization promotion will generate a large amount of carbon emissions.

(5) Industrial Structure (*IS*). The proportion of the secondary industry is indicated, i.e. the proportion of the value added of the secondary industry to the regional GDP.

(6) Energy Efficiency (*EE*). Energy consumption per unit of GDP output.

(7) Energy Consumption Structure (*ECS*). The share of coal consumption in primary energy consumption.

(8) Energy Price (*EP*). Using the industrial factory price index as a proxy variable.

(9) Clean technology level (*NF*). Expressed using the number of facilities for managing carbon emissions from buildings.

III. C. Basic Model Testing

III. C. 1) Hausman test

This paper uses a panel data model, so a Hausman test is needed before the first step of the estimation test to determine whether the model used in the regression test is a fixed effect or random effect model.The results of the Hausman test are shown in Table 3, which shows that the local fiscal final expenditures (*LFS*), trade openness (*TO*), foreign direct investment (*FDI*), and energy efficiency (*EE*), Energy Consumption Structure (*ECS*), Energy Price (*EP*), and Clean Technology Level (*NF*) using a fixed effects model. The level of urbanization (*CSH*) and industrial structure (*IS*) use random effects models.

Table 3: The result of Hausman Test

Variable	Chi-Sq.Statistic	Chi-Sq.d.f.	Prob.	Model
LFS	24.2295	5	0.0003	Fixed
TO	7.0035	5	0.0506	Fixed
FDI	20.1685	5	0.0000	Fixed
CSH	5.2402	5	0.1219	Random
IS	4.7855	5	0.1529	Random
EE	29.2044	5	0.0000	Fixed

ECS	12.0658	5	0.0043	Fixed
EP	9.7533	5	0.013	Fixed
NF	7.7812	5	0.0344	Fixed

Note:The significant level is 10%.

III. C. 2) Basic test results

On the basis of the Hausman test to determine the type of model to be used, the regression test was carried out by Eviews, and the regression results of the variables in are shown in Table 4.As can be seen from Table 4, the seven target variables, except for foreign direct investment (*FDI*) and the level of clean technology (*NF*), passed the first step of the test of the EBA (β_m >0), which indicates that there is a correlation between them and carbon emissions.

Table 4: The result and analysis of the EBA Mode

Variable	β_m	t	Prob.	Whether it passes the inspection
LFS	0.9002	-5.7582	0.0015	Yes
TO	0.0656	-0.8689	0.3234	Yes
FDI	-0.1971	1.8054	0.0952	No
CSH	0.1105	-1.0973	0.2247	Yes
IS	3.008	4.2773	0.0015	Yes
EE	0.3454	2.3572	0.0278	Yes
ECS	1.8003	6.3638	0.0028	Yes
EP	0.707	4.0114	0.0016	Yes
NF	-0.3915	2.0519	0.0564	No

Note:The significant level is 10%."Yes" indicates passing the inspection, and "No" indicates not passing the inspection

III. D. Analysis of EBA model test with different combinations of variables

Based on the content of the above analysis, this paper proposes the following variable combinations for the influencing factors of building carbon emissions:

(S1) Combination 1: energy efficiency (*EE*), energy consumption structure (*ECS*), energy price (*EP*)

(S2) Combination 2: urbanization level (*CSH*), industrial structure (*IS*)

(S3) Combination 3: trade openness (*TO*), local fiscal final expenditure (*LFS*)

The results of the EBA model test analysis of different variable combinations are shown in Table 5, among which (S1) combination 1 has the best effect, with P=0.000 for β, showing a strong significance. It can be said that the relationship between energy efficiency, energy consumption structure and energy price and carbon emissions in housing development is "strongly significant". (S2) Combination 2 has the next highest effect, with β = 0.035. (S3) Combination 3 has an average effect. Therefore, in formulating the carbon emission control strategy for housing development, emphasis should be placed on the performance of the selected energy efficiency, as well as the structure of energy consumption during the development process. In the selection of energy types, based on the development and construction needs, the new energy with environmental advantages, resource sustainability and economic benefits is the trend.

Table 5: The test results of the EBA model with different combinations of variables

Type	RMSE	r^2	$P(\beta)$
S1	5.62	0.87	0.000
S2	6.08	0.81	0.035
S3	36.6	0.23	0.049

III. E. Carbon emission control in housing development in industrial heritage clusters

Industrial and mining heritage based on mineral resources is usually presented in a collective form, called industrial and mining heritage clusters. Based on the development and construction of urbanization process, there are a few clusters of industrial and mining heritage, which can easily be placed in the urban ecological development with negative impacts that cannot be ignored, which is against the concept of sustainable development. Based on the above analysis, this section proposes the following three strategies to control carbon emissions from industrial heritage clusters in urban housing development:

(1) Improvement and protection of industrial and mining texture. For areas where the industrial and mining heritage is relatively well preserved in housing development, industrial and mining texture remediation and

protection measures are taken. Repair and restore" is taken as the main means, with 'preservation' as the main purpose. In the overall layout planning, combined with the needs of urban construction and ecological architectural concepts, follow the principles of retaining the core area, site memory, local materials, etc., to establish the core area of industrial and mining heritage protection.

(2) Industrial and mining texture remodeling protection. The original texture has been slightly or moderately damaged industrial and mining heritage clusters, through the "texture remodeling" of the relevant technical means, so that the original fuzzy, inconspicuous industrial and mining texture to restore clarity and obviousness. Specific process steps are as follows: sorting out and refining different categories of texture factors from the original texture, deconstructing the original industrial and mining texture structure, designing the corresponding spatial structure, and finalizing the final protection planning scheme.

(3) Optimize energy structure. In the housing development based on industrial heritage clusters, in addition to the need to fully protect and reshape the original industrial and mining heritage in the planning and design, it is also necessary to pay attention to the structure of energy use in further development and construction, and try to avoid the creation of large-scale industrial and mining heritage clusters. Instead, new energy sources should be utilized in conjunction with actual production needs and under the guidance of eco-architectural concepts.

IV. Conclusion

This paper adopts the carbon emission model of the construction industry as a measure of carbon emissions in housing development, uses a panel data model to carry out quantitative analysis, and uses the EBA model to test the statistical relationship between target variables and carbon emissions. Based on the carbon emissions and related data of Province I from 2010 to 2019, the seven selected target variables: local fiscal expenditure, trade openness, urbanization level, industrial structure, energy efficiency, energy consumption structure, and energy price all passed the EBA model test (β_m>0). Among the proposed combinations of variables, the combination composed of energy efficiency, energy consumption structure and energy price $P(\beta)$=0.000, and the combination composed of urbanization level and industrial structure $P(\beta)$=0.035. Accordingly, this paper puts forward three suggestions for the carbon emission control strategy of industrial heritage clusters in housing development: remediation and preservation of industrial and mining texture, remodeling and preservation of industrial and mining texture, as well as optimization of energy structure.

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