Influence of Urbanization on Carbon Emission Rights: An Analysis Based on an Enhanced Translog Production Function and Refined Urban Boundaries

Yihan Li, Linjuan Zhang, Yue Xu, Weiyu Li, Lixin Tian*

This study evaluates urbanization's impact on carbon emission rights value in China using translog production functions and carbon shadow pricing models. Firstly, the MK trend test and decoupling analysis divided the city into four carbon emission pressure types, where an enhanced translog three-factor model is used to analyze the nonlinear relationships among population, area, economic development, and total carbon emissions. The results reveal that population growth and urban expansion significantly increase carbon allowance values, with heterogeneous effects across urban types. Carbon-excessive cities demonstrate the strongest correlation, while plateau cities show minimal impacts, suggesting existing low-carbon adaptations. Notably, 50% of cities have achieved peak emissions during rapid urbanization, fulfilling emission control targets. Excessive-emission cities face urgent decarbonization pressure, requiring prioritized policy interventions, whereas plateau cities' gradual emission growth offers transferable experience for low-carbon transitions. Finally, taking the cities in Guangdong province as an example, we use the shadow price model to calculate the value of carbon emission right, and combine the marginal influence of social factors to obtain the change of carbon emission right value under the influence of urbanization. The highest was 4759.08 yuan / ton for Shenzhen and the lowest was 253.19 yuan / ton for Heyuan.

Keywords: shadow price, urbanization, city boundary correction, regional carbon trading, translog production function

1. Introduction

With the ongoing expansion of the global population and swift economic progress, urbanization has emerged as a worldwide phenomenon.Throughout the urbanization

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process, substantial carbon emissions are discharged into the atmosphere due to extensive energy consumption, transportation, construction, and industrial operations. Consequently, China has implemented a carbon emissions trading scheme, which effectively influences the value of carbon emission permits through market mechanisms and economic incentives, thereby promoting global efforts to reduce greenhouse gas emissions.

Carbon emission rights refer to the permits allocated by the government or regulatory bodies to enterprises or countries to reduce greenhouse gas emissions. It quantifies the emissions of greenhouse gases, turning them into a tradable commodity and utilizing market mechanisms to regulate and reduce greenhouse gas emissions. When an enterprise's carbon emissions are lower than its allocated quota, it can sell the surplus quotas to enterprises whose emissions exceed their quotas. There are two forms of carbon emission rights trading: one is conducted in the primary market, and the other in the secondary market. Trading in the primary market involves the allocation of carbon emission rights by relevant national departments, which is closely related to the government's pricing policies. Trading in the secondary market involves enterprises trading their held carbon emission rights in an open market. Whether in the primary or secondary market, accurately grasping the value of carbon emission rights is crucial for both the government and enterprises. The value of carbon emissions can be either the actual transaction price of carbon quotas in the market or the theoretical valuation based on an optimal planning model, namely the shadow price. The shadow price can be understood as the contribution of any marginal change in the availability of production factors to the country's fundamental objectives, such as the growth of national income. This means that the shadow price is not only influenced by the country's economic growth targets but also constrained by the environmental conditions on which the marginal changes in resource availability depend. Given that carbon emission rights are a scarce resource, their price should accurately reflect their marginal benefits, that is, the environmental benefits or economic losses brought about by an increase or decrease of one unit of carbon emission rights. Therefore, by applying the theory of shadow pricing, the value of carbon emission rights can be assessed more precisely, thereby providing a more scientific pricing basis for carbon emission rights trading.

The impact of urbanization on carbon emission rights prices materializes in the increased demand for carbon emissions and changes in supply capacity, thereby affecting the market's supply-demand equilibrium and the trajectory of carbon emission rights prices. Furthermore, governmental policy regulations play a significant role in influencing the volatility of carbon emission rights prices. This study primarily focuses on the influence of social factors within the urbanization process on the valuation of carbon emission rights. Population and area serve as intermediary variables to establish the connection between urbanization and the value of carbon emission rights. The aim is to discern the dynamic equilibrium between societal progress and a low-carbon economy through an urbanization model.

Carbon emission rights, viewed as emerging assets from an evaluation standpoint, do not fit well within traditional evaluation methods, making it challenging to accurately assess their worth. This research employs the translog production function, rooted in marginal production theory, to incorporate carbon emissions rights as a production factor in the production function. By integrating econometric empirical methods, we develop a model to evaluate the shadow price (CSP) of carbon emission rights. Quantifying the factors influencing carbon emission rights as correction indicators enhances the evaluation system.

2. Literature Review

2.1. The Dynamic Correlation of Urbanization and Carbon Emissions

To differentiate cities based on their levels of carbon emissions, trends, and economic effects, our initial approach involves categorizing cities into distinct types using these criteria. Wang *et al*. (2021) utilized the Mann–Kendall (MK) trend test method to explore the spatiotemporal characteristics of carbon emissions and their classification into types. Shan *et al*. (2022) evaluated the status of urban emission peaks and the degree of decoupling between emissions and social development indicators using the MK trend test method. They categorized cities into four types, emphasizing the diversity in urban carbon emissions resulting from variations in energy and economic structures.

In existing studies on the impact relationship between urbanization and carbon emissions, many scholars utilize scaling laws and the Scale-Adjusted Metropolitan Indicator (SAMI) for characterization (Gong *et al*., 2021). However, both methods may be vulnerable to confounding effects, particularly correlations between variables. Ribeiro *et al*. (2019) introduced a dual-factor production model framework that treats population and area as input factors in the urban development process. This framework reveals the coupling effect of population and density on emissions. The traditional Cobb–Douglas model (C-D) has the assumption of neutral technological progress, but the reality is not satisfied, and the factors of production influence each other. The translog production function is more flexible than the C-D because it does not assume fixed input elasticities and constant returns to scale. It can capture nonlinear relationships between variables, providing a more precise fit through higher-order terms (such as square and interaction terms). It is suitable for production situations with multiple input factors.

Unlike much of the existing research, which relies on provincial-level data and directly substitutes city-level data (Zhang *et al*., 2014; Xie *et al*., 2016), this article underscores the importance of examining these dynamics on a smaller regional scale (Chen and Liu, 2018). Concerning indicator selection, previous studies have extensively explored pairwise relationships among population concentration, economic growth, area, and carbon emissions. However, the combination of all four factors into a unified analytical framework for comprehensive research is limited. Therefore, our study utilizes corrected urban boundaries as the statistical area, employing an enhanced translog three-factor model to analyze the nonlinear relationships among population, area, economic development, and total carbon emissions.

2.2. Estimation of the Carbon Emission Right Value

The CSP evaluation method is currently widely employed and highly applicable to carbon asset assessment. The application of the CSP can be classified into two categories. The first employs the directional environmental distance function and its various forms. The second utilizes the production function, considering carbon emission rights as either an input factor or an undesirable output. This paper argues that if carbon emission rights are treated as an undesirable output and used as a dependent variable, their uncontrollability and high randomness make it difficult to accurately determine their price. Furthermore, the starting point of this study is to view carbon emission rights as a scarce social resource asset that significantly impacts output. Therefore, this paper chooses to incorporate carbon emission rights as a production factor, similar to capital and labor, thereby once again leveraging the advantages of the translog production function. Zhang (2022) refined the CSP model based on the translog production function and computed the CSP of secondary market carbon emissions trading rights held by Inner Mongolia Huadian Company. Gao and Liu (2021) examined the trading conditions of the carbon market in various pilot projects nationwide. Wang *et al*. (2022) propose a nonparametric approach for estimating the optimal carbon shadow price by maximizing the possibility of GDP expansion and carbon reduction simultaneously.

2.3. Factors Affecting the Value of Carbon Emission Rights

A CSP evaluation model for carbon emissions trading is established in this article, based on the national carbon market. The model aims to evaluate the intrinsic value of carbon emissions trading by analyzing the relationship between marginal abatement costs and the marginal benefits of carbon emissions trading rights. Most studies tend to overlook the theory of market supply and demand equilibrium, failing to adjust adequately for time and market fluctuations. To bridge this gap, our article adopts a quantitative approach, considering key influencing factors such as time and carbon emission allowance policies. We introduce relevant evaluation indicators to refine the assessment of carbon emissions trading rights, ensuring a more comprehensive and accurate analysis.

Figure 1 illustrates the specific technical roadmap of this article. This paper advances the theoretical development from three aspects:

Spatial reconstruction: the urban boundary correction technology is adopted to replace the administrative boundary with the global urban boundary data set, accurately depict the real spatial carrier of population density and land development, and avoid the statistical deviation of traditional administrative divisions.

Model innovation: The paper builds an enhanced Translog three-factor model, integrates the non-linear relationship between population (P), area (A), economy (G) and total carbon emission (C), and quantifies the marginal emission elasticity and interaction effect.

Dynamic pricing: The paper redefines carbon emission right as a scarce production factor, coupling market supply and demand mechanism and policy regulation through shadow price theory, introducing time calibration and quota adjustment factor, and establishing a dynamic CSP evaluation framework.

3. Study Area and Data

All 330 cities in the dataset of urban carbon emissions, as reported by the Chinese Cities Greenhouse Gas Inventory (CCG), are scrutinized in this article. The dataset covers cities across the 31 provincial-level administrative regions of China, excluding Hong Kong, Macao, and Taiwan, spanning the years 2005, 2010, 2015, and 2020.

This article utilizes urban CO_2 emission data from CCG, which computes direct and indirect CO_2 emissions of Chinese cities using the internationally prevalent carbon emission factor method, integrating it with the specific circumstances of Chinese cities, and furnishes data on carbon emissions from crucial industries. Emissions from the agriculture and rural living sectors were omitted. The Global Urban Boundary Dataset includes the boundaries of all cities and adjacent residential areas worldwide with areas exceeding 1 square kilometer.

4. Research Methods

4.1. Methods for Urban Classification

The carbon emission trend of cities over a 15-year period can, to some extent, indicate the level of green development. Due to the limited understanding of their overall distribution, we opted for a nonparametric test method known as the MK trend test. Cities are classified into four categories—significantly decreasing, decreasing, increasing, and significantly increasing——based on the direction and extent of carbon

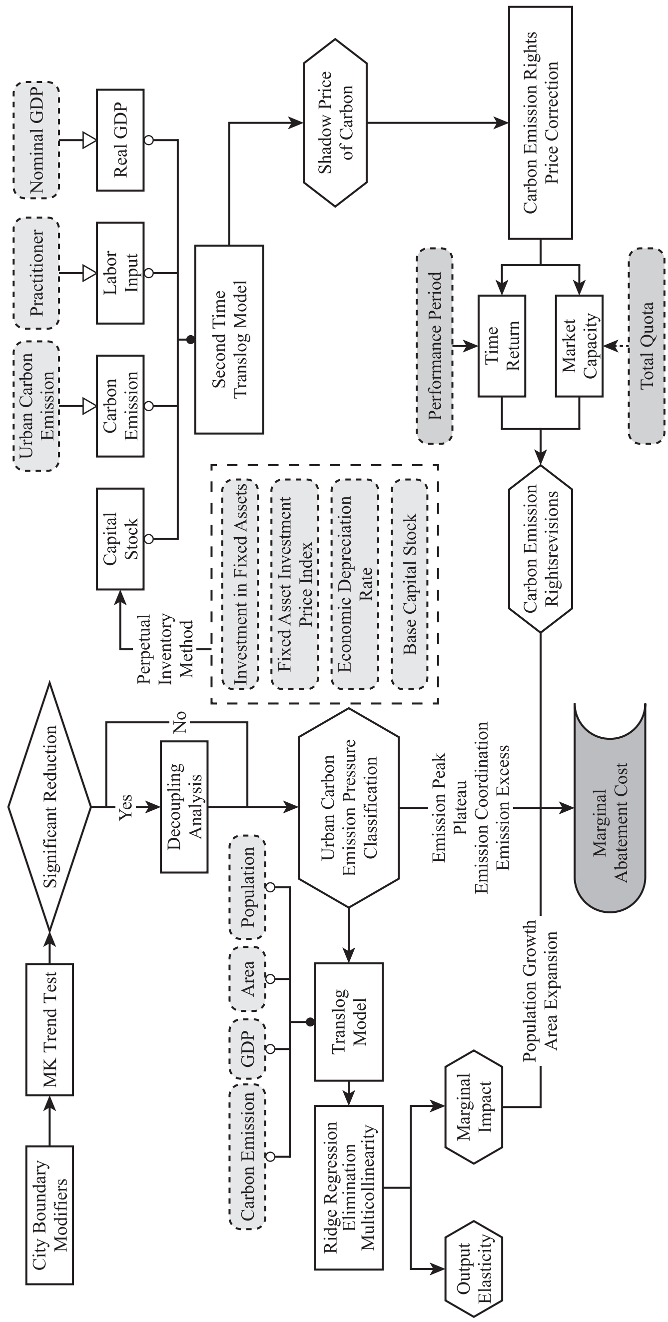

Figure 1. The Overall Framework

emission changes.

(1) The original assumption (H0) is that the time series data $(x_1, x_1, ...x_n)$ of n independent samples has the same distribution. The alternative hypothesis (H1) assumes different distributions for all $i, j \leq n$ and $i \neq j$, x_i and x_j.

(2) Calculate the test statistic S.

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_j - x_i) \tag{1}$$

(3) For time series with 10 or more data points, a normal approximation is used. The variance of the statistic S is calculated as follows:

$$var(S) = \frac{1}{18}[n(n-1)(2n+5) - \sum_{i}^{n} e_i (e_i - 1)(2e_i + 5)] \tag{2}$$

where the number of samples with the same annual carbon emissions is denoted as n, and the number of samples with different carbon emissions in samples with the same i value is denoted as e_i.

(4) Construct the standardized normal distribution variable Z using the following formula:

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{var(S)}}, & if \ S > 0 \\ 0, & if \ S = 0 \\ \dfrac{S+1}{\sqrt{var(S)}}, & if \ S < 0 \end{cases} \tag{3}$$

At a certain confidence level, if $Z \geq |Z_{1-\alpha/2}|$, the null hypothesis is rejected, indicating a significant trend in the annual carbon emissions time series at the confidence level. Here, we choose a 90% confidence interval, and the Z value is 1.64. That is, $Z > 1.64$ is considered significant; otherwise, it is not significant (Sa'adi *et al*. 2019).

(5) The magnitude of the trend is represented by the following formula:

$$\gamma = Median(\frac{x_i - x_j}{i - j}), \forall j < i \qquad 1 < j < i < n \tag{4}$$

where *Median*(.) denotes the median. $\gamma > 0$ indicates an upward trend, while $\gamma < 0$ indicates a downward trend.

For cities identified with significant increases in carbon emissions through the MK trend test, decoupling theory is applied to analyze the relationship between economic growth and carbon emissions (Hang *et al*., 2019). This is conducted to evaluate the city's ability to balance economic development and carbon pressure. The decoupling index is used to illustrate the extent and direction of "decoupling". In this study, the total amount is considered the driving variable, while carbon emissions serve as the explained variable.

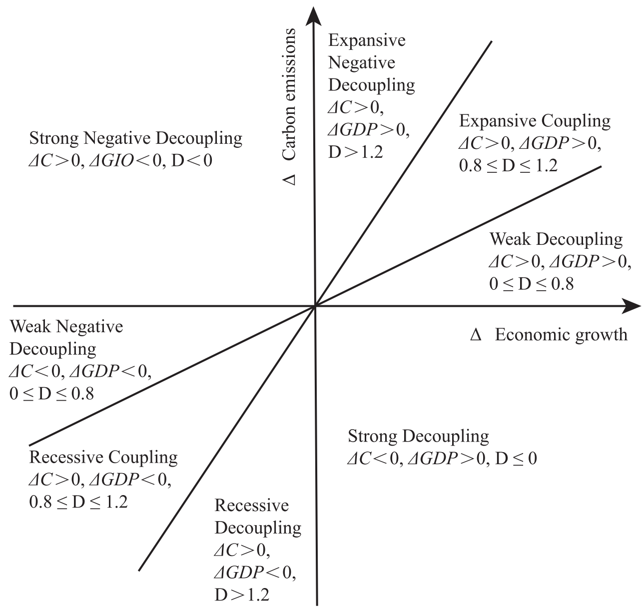

Figure 2. Evaluation Criteria for Decoupling Analysis.

Drawing from Tapio's elasticity decoupling model, the carbon decoupling index is defined as the ratio of the change rate of carbon emissions to the GDP change rate during a specific period. The calculation is as follows:

$$D = \frac{\Delta C_n / C_{n-1}}{\Delta GDP_n / GDP_{n-1}} = \frac{\left(C_n - C_{n-1}\right) / C_{n-1}}{\left(GDP_n - GDP_{n-1}\right) / GDP_{n-1}} \tag{5}$$

where D represents the decoupling elasticity coefficient, C represents carbon emissions, ΔC and ΔGDP represent the changes in carbon emissions and regional gross domestic product , n=2005, 2010, 2015, 2020.

This paper conducts a comprehensive assessment of the relationship between carbon emissions and the level of urban economic development, categorizing the degree of decoupling between the two into eight criteria. The criteria include empirical values for judgment thresholds of 0.8 and 1.2, as depicted in Figure 2. To prevent overidentification, elasticity values of 1 and those within ±20% deviation are considered (Tapio, 2005).

Using the results of the decoupling analysis, cities are categorized into four groups, as illustrated in Figure 3: emission peak, plateau, emission coordination, and emission excess, representing varying levels of carbon emission pressure. The emission peak category comprises cities where carbon emissions do not notably decrease; the emission plateau category includes cities where carbon emissions experience slow growth or no significant increase; the emission coordination category involves cities with weak decoupling; and the emission excess category includes cities characterized by expansion connections, strong negative decoupling, and expansion negative decoupling.

4.2. Three-Factor Production Function Model

In the actual scenario, the influence of explanatory variables on the explained variable is not related to individual factors alone, but is intertwined with other factors that affect the explanatory variable. In a hyperlogarithmic function, inputs are conceptualized as three abstract entities: population, GDP, and area. The additional flexibility brought by the interaction term between the three social factors quantifies the intensity of this interaction, so that the impact of social factors on emissions varies with the changes of P、A and G, and the output represents the carbon emissions of the city affected by the three factors.

$$\begin{aligned} &C = f(P, A, G, T) \\ &\ln C = \alpha + \beta_1 \ln P + \beta_2 \ln A + 0.5\beta_{11}(\ln P)^2 + 0.5\beta_{22}(\ln A)^2 \\ &+0.5\beta_{33}(\ln G)^2 + \beta_{12}(\ln P)(\ln A) + \beta_{13}(\ln P)(\ln G) \\ &+\beta_{23}(\ln A)(\ln G) + \beta_t T + 0.5\beta_{tt} T^2 \end{aligned} \tag{6}$$

where C represents the total carbon emission of the city (comprising both indirect and direct carbon emissions), P denotes the urban population, A signifies the corrected urban area, G stands for the gross domestic product, and T represents the time trend item, with assigned values of 5, 10, 15, and 20, respectively. a and β_i are coefficients associated with the input, representing the primary impact of each input variable on carbon emissions in the short term. If β is significant and positive, the input variable positively influences the increase in carbon emissions; otherwise, the opposite holds; β_{ii} is the squared coefficient of the input factor, reflecting the long-term impact on carbon emissions; β_{ij} is the cross term of the input factors, illustrating the influence of the interaction between two input variables on carbon emissions; β_t and β_{tt} are utilized to compare changes between different years horizontally.

Considering the correlations among population, area, and GDP, accurately estimating the model is challenging and may suffer from multicollinearity. The variance inflation factor (VIF) for each type of data for each year was systematically examined. The results indicated significant multicollinearity in all 16 groups of data. Given the substantial correlation among explanatory variables, ridge regression was applied to each dataset to alleviate the impact of multicollinearity on the model (Lin and Atsagli, 2017).

The output elasticity serves as a measure to assess the strength of the relationship between the input and the output. Descriptive statistical analysis was conducted on the four types of urban data for each year. The corresponding output elasticity was calculated by substituting the fitted coefficient values and the arithmetic mean of each input factor into the following formula:

$$\begin{aligned}
\frac{\partial C / C}{\partial P / P} &= \frac{\partial \ln C}{\partial \ln P} = \beta_1 + \beta_{11}\ln P + \beta_{12}\ln A + \beta_{13}\ln G \\
\frac{\partial C / C}{\partial A / A} &= \frac{\partial \ln C}{\partial \ln P} = \beta_2 + \beta_{22}\ln A + \beta_{12}\ln P + \beta_{23}\ln G \\
\frac{\partial C / C}{\partial G / G} &= \frac{\partial \ln C}{\partial \ln G} = \beta_3 + \beta_{33}\ln G + \beta_{13}\ln P + \beta_{23}\ln A
\end{aligned} \tag{7}$$

The marginal impact signifies the percentage alteration in carbon emissions resulting from a one-unit change in a single factor while keeping other input factors constant.

$$\begin{aligned}
\frac{\partial C / C}{\partial P} &= \frac{\partial \ln C}{\partial P} \\
\frac{\partial C / C}{\partial A} &= \frac{\partial \ln C}{\partial P} \\
\frac{\partial C / C}{\partial G} &= \frac{\partial \ln C}{\partial G}
\end{aligned} \tag{8}$$

4.3. Shadow Price Calculation

Among the trial of carbon trading markets in China, Guangdong's carbon trading market offers the highest cumulative trading volume and total transaction value, surpassing 100 million tons in cumulative trading volume. Hence, we incorporated the 21 prefecture-level cities in Guangdong Province and calculated the marginal emission reduction costs at the city level.

This paper introduces the translog production function to refine the shadow pricing method, with input variables comprising capital stock (*K*), labor input (*L*), and carbon emissions (*E*), and the output variable (*Y*) being actual GDP. The transcendental logarithmic production function is expressed as follows:

$$\begin{aligned}\ln Y_t &= \varepsilon + \alpha_K \ln K_t + \alpha_L \ln L_t + \alpha_E \ln E_t + \alpha_E \ln E_t \\ &+\alpha_{KL} \ln K_t \ln L_t + \alpha_{KE} \ln K_t \ln E_t + \alpha_{LE} \ln L_t \ln E_t + \alpha_{KL} \ln K_t \ln E_t \\ &+\alpha_{KK} \left(\ln K_t\right)^2 + \alpha_{LL} \left(\ln L_t\right)^2 + \alpha_{EE} \left(\ln E_t\right)^2\end{aligned} \tag{9}$$

The expression of China's carbon emission CSP P_t can be expressed as

$$P_t = \frac{Y_t}{E_t}(\alpha_E + \alpha_{KE} \ln K_t + \alpha_{LE} \ln L_t + 2\alpha_{EE} \ln E_t) \tag{10}$$

The calculated sample CSP is weighted and averaged to obtain the social marginal emission reduction cost, which is the CSP P of the national carbon emission right:

$$P = \sum_{i=1}^{n} P_i \Big/ n \tag{11}$$

This study mainly uses the perpetual stock system to estimate capital stock:

$$K_t = I_t / P_t + \left(1 - \delta_t\right) K_{t-1} \tag{12}$$

where K_t is the capital stock in year t , I_t is the new investment in year t , P_t is the investment price index in year t, and δ_t is the capital depreciation rate in year t.

Assuming diminishing marginal efficiency, estimating capital stock through the perpetual stock method involves considering four variables: fixed asset investment amount (I_t), fixed asset investment price index (P_t), economic depreciation rate (δ_t), and base period capital stock (K_t). δ_t utilizes an empirical value of 9.6% provided by Zhang (2004).

Typically, the choice of the investment price index relies on the national fixed asset investment price index. However, due to significant missing data for certain years and regions, Zhang *et al*. (2004) attempted to substitute the missing fixed asset investment price index with the investment implicit deflator index. Consequently, some studies have begun to adjust the nominal value of capital stock using the GDP deflator index (*GDI*). This ensures availability through the completeness of the GDP series and *GDP* index (*GI*) series, aligning with the statistical caliber of the current year's new capital stock series. This consistency is crucial as final consumption, gross fixed capital formation, and net exports of goods and services constitute the entire content of expenditure-based GDP.

$$GDI = \frac{GDP_n}{GDP_{n-1} \times GI_n} \tag{13}$$

The regional *GI* for each city was gathered from 2000 to 2020. The data was adjusted to establish the *GI* with 2000 as the fixed base period.

Building upon Shan(2008)'s expanded calculation formula for the base capital stock, which assumes "the growth rate of capital stock under economic steady-state conditions is equal to the growth rate of investment," the formula is as follows: Base capital stock = Total capital formation / (Uniform depreciation rate + Average growth rate of fixed asset formation). In this investigation, the total fixed asset formation in 2000 was divided by the depreciation rate and the average growth rate of fixed asset formation from 2000 to 2020.

$$K_1 = \frac{I_2}{g+\delta} \tag{14}$$

The labor input indicator in each city of Guangdong Province for the current year utilizes the number of employed individuals. Data are sourced from the annual statistical yearbooks of various regions and are measured per ten thousand people. Labor input is derived from end-of-period data on urban employees, excluding rural and suburban areas. To mitigate the influence of prices on the model's errors, it is essential to transform nominal GDP into real GDP. This study employs the GDP deflator method. GDP conversion results are shown in the Appendix on the Journal's website.

4.4. Carbon Emission Allowance Value Adjustment

In the national carbon trading market, the compliance period typically spans one year, and the quotas allocated to enterprises for free undergo verification in the subsequent year. Any remaining carbon emission allowances can be traded on the secondary market. Buyers of these allowances must utilize them before the next compliance period, as government confiscation may occur upon expiration, leading to economic losses. Hence, the closer the compliance deadline is, the lower the value of carbon emission allowances will be. There exists a lag effect between purchasing the allowances and employing them for production. Thus, it becomes necessary to adjust for the changes in carbon emission benefits resulting from this lag period.

Assuming a one-year compliance period for carbon emissions in Guangdong Province, the annual production capacity of a unit of carbon emission allowance is evenly distributed on a monthly average basis. T denotes the time from the evaluation base date to the announcement date of the CSP of carbon emission allowances. According to market research data from the Guangdong Emission Trading System, the deadline for quota surrender for control-emission enterprises in Guangdong Province in 2020 was July 20th, with the latest price negotiation release date being August 2nd. Therefore, T is 13 days, approximately 0.42 months. The adjusted value of carbon emission allowances is computed as follows.

$$W = \frac{P \times (12 - T)}{12} \tag{15}$$

The influence of policy effectiveness on the value of carbon emission allowances is critical. However, due to the intricate and unquantifiable nature of policy effects, this paper exclusively examines policies regulating the supply and demand of carbon emission allowances in the trading market. These policies primarily involve the total quota of carbon emission allowances and their impact on the market. When the government reduces the total quota of carbon emission allowances, the supply of quotas on the carbon emission allowance trading market decreases in the short term due to enterprises' inability to innovate in production and emission reduction technologies. Consequently, this affects the price of carbon emission allowances. During such periods, the calculated CSP should consider the impact of the policy-induced supply-demand imbalance and adjust it to determine the final assessed value. S represents the total annual quota announced by the government, i.e., the market carbon emission right capacity, S_{t-1} is the carbon emission market capacity of the previous period, S_t is the carbon emission market capacity of the current period.

$$W_t = \frac{P \times S_{t-1}}{S_t} \times 100\% \tag{16}$$

According to data from the Guangdong Carbon Trading Market, the total carbon quota was 465 million tons in 2019 and 464 million tons in 2020. In this study, the carbon reduction target in Guangdong Province in 2019, considered the carbon emission market capacity (MC) before carbon peaking, is regarded as 1. It is assumed that there will be no supply exceeding demand for carbon emission allowances in the market before reaching the peak. Therefore, the adjusted market capacity for carbon emission allowances in 2020, after adjusting for the total quota, is 99.7% of the capacity in 2019. The adjusted price for carbon emission allowances is calculated accordingly.

$$W = P \times \frac{MC_{2019}}{MC_{2020}} \times 100\% \tag{17}$$

5. Results

5.1. Marginal Effects of Carbon Emissions

Following the application of the classification model, we categorized the 330 cities into four groups, as depicted in the Appendix online, based on their carbon emission levels, trends, and decoupling situations. These four types are arranged in ascending order of carbon emission pressure faced by the cities. The first category, comprising 162 cities, is termed “emission peak,” indicating that carbon emissions do not notably decrease. The second category, consisting of 42 cities, is labeled as “plateau cities,” where carbon emissions increase slowly or show no significant increase. The third category, comprising 93 cities, is referred to as “emission coordinated cities,” wherein both economic growth and carbon emissions increase, or economic growth slightly outpaces carbon emissions. Finally, the fourth category, including 33 cities, is termed “emission exceeded cities,” indicating that carbon emission pressure surpasses the economic growth rate. The population, area, and GDP of the four major cities are shown in the Appendix online.

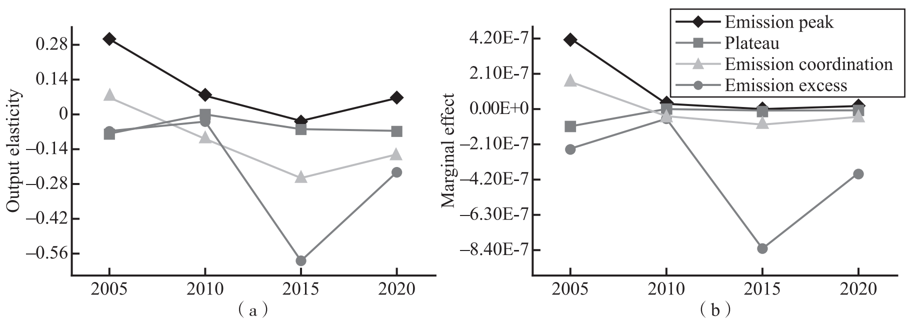

Figure 3. Output Elasticity and Marginal Impact of Population

Figure 3 illustrates that from 2005 to 2010, the average output elasticity of population and carbon emissions exhibited a decreasing trend for emission peak and emission coordinate cities, transitioning from positive to negative values for emission coordinate cities. This implies that increasing each input results in an increase in output. Plateau and emission exceeded cities showed relatively stable changes, with all cities demonstrating a negative correlation, indicating that population growth leads to a decrease in carbon emissions. Between 2010 and 2015, the most significant change

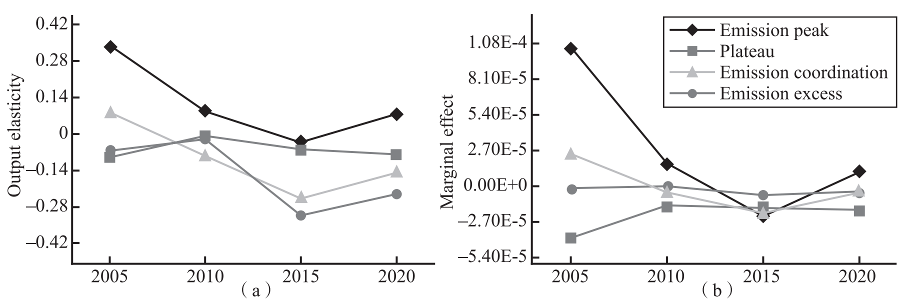

Figure 4. Output Elasticity and Marginal Effects of Area

occurred in emission exceeded cities, witnessing a sharp drop in output elasticity, while other types showed a slight decrease, all declining to negative values. From 2015 to 2020, all city types except plateau cities rebounded, including emission exceeded cities. Over time, the overall output elasticity of population and carbon emissions demonstrates a decreasing trend, signifying a weakening correlation between population changes and carbon emissions.

From Figure 4, concerning the overall level of output elasticity, the output elasticity of population growth and that of area expansion exhibit a similar trend across all city types. The marginal impacts of the two indicators differ significantly, with urban expansion resulting in notably more carbon emissions than population growth. In 2015, both indicators exhibited negative effects, indicating that area expansion led to a decrease in carbon emissions. These negative effects weakened by 2020. The emission peak underwent a sharp decline from 2005 to 2015 before gradually rebounding, while emission exceeded cities remained at a relatively low level.

5.2. Shadow Price Examples in Guangdong Province

We conducted logarithmic, squared, and cross-multiplication transformations on the fundamental data for Guangdong Province to integrate them into the translog production function (refer to the Appendix online).

The output elasticities of various input factors are depicted in Figure 5. These elasticities for all factors exhibit a fluctuating downward trend, indicating a gradual weakening contribution of these input factors to economic growth. Notably, carbon emissions display the smallest output elasticity, suggesting significant potential for its impact on economic growth.

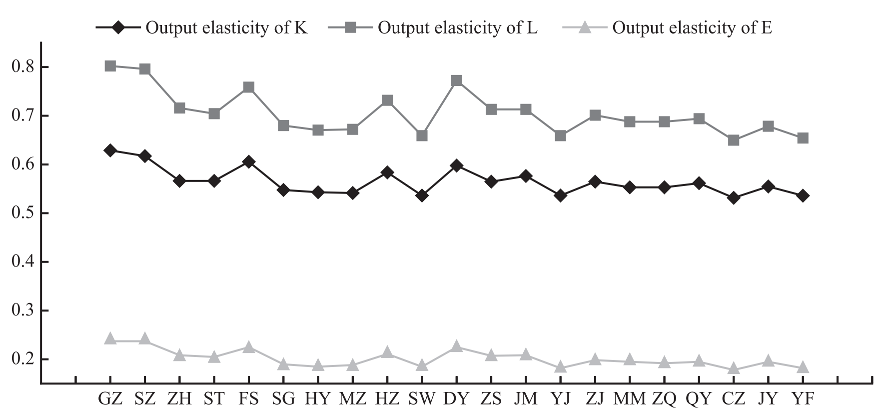

Figure 5. The Output Elasticity of Factors

5.3. Shadow Price Adjustment

Table 1. CSP of Cities in Guangdong Province in 2020

City	Shadow price (yuan/ton)	City	Shadow price (yuan/ton)
Guangzhou	2690.70	Zhongshan	1056.28
Shenzhen	4921.09	Jiangmen	951.31
Zhuhai	1171.50	Yangjiang	395.52
Shantou	817.77	Zhanjiang	487.17
Foshan	1766.97	Maoming	1550.30
Shaoguan	277.72	Zhaoqing	465.57
Heyuan	261.81	Qingyuan	263.22
Meizhou	331.03	Chaozhou	490.17
Huizhou	331.03	Jieyang	827.97
Shanwei	976.59	Yunfu	334.65
Dongguan	1275.71	Average	1042.32

According to Table 1, the CSP of carbon emissions across various municipal cities in 2020 were assessed. Guangzhou, Shenzhen, Zhuhai, Foshan, Huizhou, Zhongshan, Jiangmen, and Zhaoqing exhibited relatively high CSP of carbon emissions, indicating that these areas would face increased economic costs to accomplish additional carbon reduction. Shenzhen recorded the highest CSP at 4921.09 yuan/ton, while Shaoguan recorded the lowest CSP at 277.72 yuan/ton.

The shadow price difference of carbon emission rights between Shenzhen and Shaoguan is as high as 17 times. This phenomenon is the result of the multiple effects of regional economic structure, energy efficiency and market mechanism. The specific driving reasons include the fundamental differences between economic development stage and industrial structure, the regional differentiation of carbon market activity and policy implementation intensity, the great contrast between energy structure and green technology penetration, and the policy effect of spatial constraints and ecological red line.

Since the emission reduction technology and policy is changing, the shadow of carbon emissions price also experiences constant change and gradually deviates from the real carbon emissions intrinsic value, leading to huge error in the assessment results. When comparing the CSP before and after adjustment in Table 1 and Table 2, it is observed that Shenzhen's CSP decreased by 172.24 yuan due to time adjustment and by 162.01 yuan due to market adjustment. Similarly, Shaoguan's CSP decreased by 9.72 yuan due to time adjustment and by 9.14 yuan due to market adjustment. This suggests that cities with higher CSP experience a larger difference before and after adjustment, indicating a greater impact from time and market factors.

Table 2. Revised Shadow Price of Cities in Guangdong Province

City	Time calibration	Market modification	City	Time calibration	Market modification
Guangzhou	2596.52	2602.12	Zhongshan	1019.31	1021.51
Shenzhen	4748.85	4759.08	Jiangmen	918.02	920.00
Zhuhai	1130.50	1132.93	Yangjaing	381.68	382.50
Shantou	789.15	790.85	Zhanjiang	470.12	471.13
Foshan	1705.12	1708.80	Maoming	1496.04	1499.27
Shaoguan	268.00	268.58	Zhaoqing	449.37	450.34
Heyuan	252.65	253.19	Qingyuan	254.01	254.56
Meizhou	319.44	320.13	Chaozhou	473.01	474.03
Huizhou	942.41	944.44	Jieyang	798.99	800.72
Shanwei	555.49	556.69	Yunfu	322.93	323.63
Dongguan	1231.06	1233.71			

The main reason why the calculated shadow price of carbon emission right gradually deviates from its intrinsic value over time is the dynamic complexity of carbon emission right pricing. On the one hand, technological progress and policy iteration directly change the supply and demand relationship of carbon emission rights. For example, clean energy technology breakthrough may reduce the cost of enterprise emission reduction and thus reduce the demand for carbon emission rights. On the other hand, the adjustment of carbon market mechanism design (such as quota allocation method and market coverage) will reshape the price formation mechanism. Time adjustment reflects the structural decline of emission reduction cost under the long-term trend, while market adjustment reflects the repair effect of short-term imbalance between supply and demand. The combined action of the two leads to the amplification of the adjustment range of cities with high shadow price.

Appendix online shows the marginal impact of carbon emission reduction in Guangdong in 2020. Table 3 illustrates that the marginal abatement costs for carbon emissions in various cities in Guangdong province in 2020 were all positive, suggesting that increases in population and area led to a rise in the value of carbon emission allowances. The highest marginal abatement cost resulting from population changes was 3.53×10^{-5} in Heyuan, while the lowest was 2.49×10^{-9} in Shenzhen. Regarding area expansion, the highest marginal abatement cost was 973.22 in Yunfu, with the lowest being 9.27 in Guangzhou. The marginal abatement cost attributed to population in each city in Guangdong province was less than that for area, indicating that fluctuations in the value of carbon emissions allowances driven by population growth are more pronounced than those driven by area growth.

Table 3. Marginal Cost of Emissions Reduction in Each City in Guangdong Province in 2020.

City	Marginal cost (Population) (person/ton)	Marginal cost (Area) (km^2/ton)	City	Marginal cost (Population) (person/ton)	Marginal cost (Area) (km^2/ton)
Guangzhou	$4.36e^{-09}$	9.27	Zhongshan	$3.43e^{-09}$	57.25
Shenzhen	$2.49e^{-09}$	9.70	Jiangmen	$2.01e^{-07}$	87.23
Zhuhai	$9.77e^{-08}$	219.11	Yangjaing	$2.93e^{-08}$	766.26
Shantou	$2.62e^{-06}$	87.38	Zhanjiang	$2.36e^{-08}$	326.43
Foshan	$2.74e^{-06}$	15.80	Maoming	$1.97e^{-06}$	164.27
Shaoguan	$2.22e^{-05}$	774.04	Zhaoqing	$2.85e^{-08}$	347.39
Heyuan	$3.53e^{-05}$	912.75	Qingyuan	$4.40e^{-07}$	522.92
Meizhou	$4.04e^{-08}$	670.64	Chaozhou	$4.67e^{-06}$	266.00
Huizhou	$1.28e^{-08}$	56.05	Jieyang	$1.07e^{-06}$	95.38
Shanwei	$2.42e^{-08}$	388.63	Yunfu	$1.28e^{-05}$	973.22
Dongguan	$9.98e^{-09}$	23.98			

6. Conclusions and Policy Implications

This study aims to explore how population growth and area expansion affect the value of carbon emission allowances amid urbanization. By applying marginal production theory and treating carbon emission allowances as production factors, the research employs the translog production function to quantify their influence. The objective is to develop a CSP evaluation model for carbon emission allowances under different urban carbon emission pressures.

The analysis reveals that currently, half of China's cities are categorized as carbon peak cities, suggesting effective control over total carbon emissions despite rapid urban development. Overall, there is a positive correlation between societal factors and the value of carbon emission allowances in China. Among these factors, carbon-excessive cities experience the most significant impact on the value of carbon emission allowances from societal factors, while plateau cities are least affected. Several factors contribute to this scenario:

In light of the dual-carbon target, the government must implement measures to restrict total carbon emissions and gradually reduce the supply of carbon emission allowances. As urban populations and areas expand, enterprises require additional carbon emission allowances to meet their growing demands. However, government-imposed supply constraints exacerbate the scarcity of carbon emission allowances, thereby increasing their value.

When carbon emission pressure surpasses economic growth, regions require stronger measures to curb carbon emissions and achieve carbon neutrality or reduction goals. Urban population and area expansion lead to increased economic activities and energy consumption, resulting in a significant rise in carbon emissions. This boosts the demand for carbon emission allowances; thus, substantially elevating their value.

Regions experiencing significant carbon emissions pressure may witness an increased trading activity in the carbon emissions allowance market due to the population and area expansions. This increased trading can contribute to the escalation of carbon emission allowance values.

Plateau cities might adopt proactive measures for carbon reduction, such as advocating for clean energy and implementing carbon trading mechanisms. These efforts assist in controlling overall carbon emissions to some degree by curbing the surge in demand for carbon emission allowances and mitigating abrupt increases in their value.

Current carbon trading market has limited regulation effect on excessive emission cities, so policy tools should be combined with differentiation, such as regional carbon emission cap and industry access limit to enhance the binding force; for cities with carbon emission peak, emission reduction effect should be consolidated through low carbon technology subsidies or green finance to avoid the total rebound; plateau and coordinated cities can explore market incentive mechanisms to further improve emission reduction efficiency. By building a quota exchange circle in urban agglomerations, cross-city trading quotas are allowed, but a 5%–10% "cooperative adjustment fee" will be levied on high-carbon industries such as thermal power and chemical industry.

For the four categories of cities, the step emission reduction target is formulated to avoid "one size fits all" policy. We should promote carbon quota auction and dynamic baseline adjustment in cities with excessive emission, enhance the inhibitory effect of carbon price on urbanization expansion, and strengthen the carbon price signal, implement hard constraints on carbon emissions by different industries, and set a five-year reduction target on heavy industries (steel, cement, etc.). The carbon emission baseline of energy-intensive industries should be tightened by 3%–5% every year, and enterprises that fail to meet the standards should purchase quotas according to the difference. We should promote the upgrading of plateau cities to coordinated type through financial support, accelerating the low-carbon transformation of energy and industrial structure, and promoting technology-driven decoupling. Hence, the carbon emissions allowance market serves as just one tool for carbon reduction and should be supplemented with other measures to comprehensively advance low-carbon transformation. Cities should prioritize the promotion of low-carbon development and improve efforts in carbon emissions control, avoiding over-reliance on the carbon emissions allowance market mechanism alone.

This research also has some limitations. The research mainly focuses on the impact of supply and demand policies on the value of carbon emission rights, but in practice, the operation of carbon emission rights market is also affected by many other policy factors, such as carbon tax policy and renewable energy subsidy policy. The combination of these policies and the uncertainty of policy changes may have an important impact on the results of the value assessment of carbon emission rights, which are not fully considered in the study. The urban GHG emissions data used in the study cover only the four years of 2005, 2010, 2015 and 2020, with long time intervals, and may not fully capture the dynamic process of urban carbon emissions, especially in terms of changing trends and short-term fluctuations between adjacent years.

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