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The Carbon Emission Reduction Effects of the Quality and Quantity of R&D Activities: Evidence from Chinese Provinces

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Abstract: Research and Development (R&D) have significant impacts on carbon emissions, yet the specific data on R&D capital stock and carbon emissions have not been released by Chinese officials, hindering in-depth analysis. In light of this, this study calculates the R&D capital stock of Chinese provinces based on the SNA2008 framework and the BEA method, and estimates the carbon emissions from energy consumption and cement production using the carbon emission factor method. It then examines the carbon emission reduction effects of the quality and quantity of R&D activities at the provincial level. We find that the quality of R&D activities has a significant carbon emission reduction effect, which is stronger in regions with high levels of economic growth and marketization, and this effect strengthens over time. Moreover, mechanism analysis shows that both the quality and quantity of R&D activities reduce carbon emissions by promoting industrial structure upgrading. This paper expands the analytical approach and framework for the carbon reduction effects of R&D activities and offers significant policy and practical implications.

Keywords: R&D capital stock; carbon emissions; carbon emission reduction effect; industrial structure upgrading

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1. Introduction

Technological innovation is a key driver for carbon emission reduction. On one hand, technological innovation reduces carbon emissions through the development of green technologies. For instance, by developing energy technologies and low-carbon technologies such as carbon capture and storage, it improves energy efficiency and carbon dioxide capture efficiency; by accelerating the development of new energies, it facilitates the substitution of traditional energy with non-fossil energy. On the other hand, technological innovation reduces carbon emissions by promoting the optimization and adjustment of industrial structure. It fosters the emergence of new low-carbon industries and extends industries towards the higher end of the value chain that focuses on basic research and original innovation. This leads to the development of the service sector and a technology-intensive manufacturing industry, reducing the proportion of high-consumption, high-emission, and low-end industries in the national economy.

Research and (Experimental) Development (R&D) is at the forefront of technological innovation processes, focusing on the creation and application of new knowledge and technologies. It forms the core and foundation of technological innovation. According to the System of National Accounts 2008 (SNA2008), R&D expenditures refer to the value of resources spent on systematic creative work aimed at increasing the stock of knowledge and using this stock to develop new applications. The asset nature of R&D is increasingly prominent, but China still lacks related official data. Although the essence of R&D as an investment is acknowledged, corporate R&D has been treated as intermediate consumption rather than capital in long-term statistical accounting practices, due to the lack of related data and inconsistencies in parameter settings. Under this accounting rule, corporate R&D expenditure is an offset item of GDP, which neither accurately reflects the promotional effect of R&D on economic growth nor objectively reflects the economic value of R&D. After years of research, SNA2008 proposed for the first time that R&D should be capitalized and classified as an intellectual property product, listed under fixed capital. According to the accounting principles of SNA2008, R&D expenditures are no longer treated as intermediate consumption but as capital formation included in GDP. In recent years, China has been advancing the standardization of R&D statistical work, but has not yet published R&D capital investment data, nor established an R&D capital accounting system, making it difficult to carry out detailed accounting and analysis. Fortunately, some research has investigated the estimation issues of R&D capital stock and provided valuable insights [1–6].

An increasing number of scholars are beginning to analyze the impacts of R&D on carbon emissions. Cao and Qu [7] took provincial data from China between 1995 and 2010 as their research subjects. Under a total factor framework, they calculated and analyzed the carbon emission performance of Chinese provinces, finding that enhancing the level of R&D investment could effectively improve carbon emission performance. Shao et al. [8] extended the Logarithmic Mean Divisia Index (LMDI) decomposition model to analyze all industrial sectors in Shanghai from 1994 to 2011, and discovered that R&D investments help reduce carbon emissions. Luan et al. [9], based on panel data of the Chinese industrial sector from 2000 to 2010 and using a dynamic panel regression model for analysis, also found that R&D activities contribute to a reduction in carbon emissions. Yu and Xu [10] established a Panel-Corrected Standard Errors (PCSE) model based on industrial panel data of Chinese provinces from 2000 to 2017. They found that the intensity of industrial R&D investments can reduce industrial carbon emissions, and increasing the intensity of industrial R&D investment by 1% could improve industrial carbon emission efficiency by about 27.2%. Wen et al. [11], based on panel data from the construction industry in 30 provinces of China from 2000 to 2015, found that increasing the input of technical talents and equipment helps reduce carbon emissions in the construction industry. Wang and Zhang [12] employed the Fully Modified Least Squares method to examine the relationship between R&D investment and carbon emissions in the BRICS countries from 1996 to 2014, finding that increasing R&D investment helps decouple economic growth from environmental pressure, with the carbon reduction effect of China's R&D investment being the most significant. Lin and Xu [13], based on provincial panel data from 1990 to 2017 and using a non-parametric additive regression model, studied the impact of R&D investment on regional carbon emissions, finding that the impact of R&D investment on carbon emissions varies by region, with a U-shaped impact in the central region, an inverted N-shaped impact in the western region, but no significant impact in the eastern region.

In summary, numerous studies have analyzed the carbon reduction effects of R&D, but the indicators used are primarily R&D expenditures or R&D intensity, which inherently follow the cash basis of accounting [14]. The cash basis of accounting, also known as the cash system or cash method, is a way of recording financial transactions for individuals or businesses according to actual cash flows. Under this method, revenues are recognized when cash is received, and expenses are recognized when cash is paid. This contrasts with the accrual basis of accounting, which records transactions when they occur, regardless of cash flow. To enhance the accuracy and effectiveness of our analysis, this paper employs the R&D capital stock indicator based on the accrual basis of accounting to explore the impact of R&D on carbon emissions. By integrating the Kaya identity and the STIRPAT model, we develop an improved analytical model to investigate the carbon reduction effects and evolutionary trends of R&D activities' quantity and quality at the provincial level. We hypothesize that the quality of R&D activities has a negative impact on carbon emissions, whereas their quantity does not. This paper expands the analytical approaches and frameworks for the carbon reduction effects of R&D, providing empirical evidence and references for theoretical models, and offering decision-making references for targeted strategic deployment and policy formulation.

2. Materials and Methods

2.1. Measurement of R&D Capital Stock

The methods for measuring the R&D capital stock are similar to those used for physical capital stock. The main methods employed in related research are the PIM method, the Griliches method, and the BEA method. These methods implicitly assume that the effective proportion of capital goods declines in a geometric depreciation pattern, which simplifies the model, and equates productive capital stock with wealth capital stock. The Perpetual Inventory Method (PIM) calculates the stock of physical capital by accumulating assets acquired during different periods. According to this method, the ending stock equals the sum of the beginning stock, current investment, and current depreciation. In contrast to the PIM, the Griliches and BEA methods differ as follows: The Griliches method posits that there is a time lag in transforming internal expenditures on R&D into R&D investments. Hence, it makes adjustments to the current R&D investment amounts based on the PIM. The BEA method assumes that R&D inputs represent a continuous investment and considers depreciation to occur continuously throughout the year, thereby adjusting the current depreciation in the PIM method accordingly. We believe that the BEA method is more aligned with the intrinsic logic of economic development and of greater practical significance, also enhancing the international comparability of the estimation results. Therefore, we select the BEA method to measure the R&D capital stock, with the formula being as follows:

$$RDK_{it} = (1 - \delta_{it})RDK_{i,t-1} + \left(1 - \frac{\delta_{it}}{2}\right)RDI_{it}, \tag{1}$$

where RDK_{it} and $RDK_{i,t-1}$, respectively, represent the R&D capital stock of the target entity i in period t and $t-1$, δ_{it} is the depreciation rate of R&D assets for target entity i in period t, and RDI_{it} is the actual increase in R&D capital investments for target entity i in period t. This method assumes continuity in R&D investment within the year and that depreciation also occurs continuously, thus applying depreciation to half of the new R&D investment. When estimating R&D capital stock using this method, it is necessary to determine four key parameters: the current R&D investment amount, the R&D asset price index, the R&D asset depreciation rate, and the initial R&D capital stock.

2.1.1. Current R&D Investment Amount

Given that this paper directly estimates costs while adopting a full capitalization model, the current R&D investment is numerically equal to R&D activity inputs. Here, we only introduce how to adjust intramural expenditure on R&D into R&D activity inputs. First, to avoid double counting, we need to deduct software R&D expenses from the intramural expenditure on R&D. Second, to ensure that the accumulated fixed capital stock belongs to productive assets, we need to deduct the land value from the asset expenditures. Third, to estimate the consumption of fixed capital, we need to calculate the fixed capital stock accumulated in R&D activities based on the PIM method, with the formula:

$$K_{it} = (1 - \theta_{it})K_{i,t-1} + I_{it}, \tag{2}$$

where K_{it} and $K_{i,t-1}$, respectively, represent the fixed capital stock accumulated in R&D activities by the target entity i in period t and $t-1$, θ_{it} represents the depreciation rate of target entity i in period t, and I_{it} represents the actual new investment of target entity i in period t. The new investment numerically equals the asset expenditure in the adjusted intramural expenditure on R&D, and can be converted to the actual new investment I_{it} by deflating it with the fixed asset investment price index. Regarding the depreciation rate, following the practice of Shan [15] and Wang and Wang [3,16], we assume a residual value rate of 4%—the midpoint of China's statutory residual value rate for fixed assets of 3–5%, assuming the service lives of buildings, equipment, and other assets to be 38 years, 16 years, and 20 years, respectively. We calculate the corresponding depreciation rates using a geometric declining balance method, and weight them according to the proportions of construction installation, equipment and tool purchases, and other assets in the target entity's annual fixed asset investment, to compute the depreciation rate θ_{it} of the target entity i in period t. For the initial fixed capital stock, drawing on the approach of Hall et al. [17] and Shan [15], assuming the growth rate of capital stock is the same as the investment growth rate under a steady economic state, the initial fixed capital stock $K_{i0} = I_{i1} / \left(\overline{g}_i + \overline{\theta}_i\right)$, where I_{i1} is the actual new investment amount of the target entity i in the first year, $\overline{g}_i$ is the average growth rate of actual investment amounts including I_{i1} over a continuous five-year period (calculated using the geometric mean), and $\overline{\theta}_i$ is the average depreciation rate over a continuous five-year period including the initial year. Finally, adding the fixed capital stock accumulated in R&D activities by the target entity i to the routine expenditure in the intramural expenditure on R&D yields the R&D activity inputs. Here, labor cost and other routine expenditures are, respectively, deflated using the R&D personnel wage price index and the industrial producer purchase price index.

The treatment of software R&D expenses and land value is as follows: The first step is to exclude software R&D expenses. Jiang and Sun [18] used the proportion of intramural expenditure on R&D of software companies to the total intramural expenditure on R&D of companies in 2009 from the "Compilation of the Second National R&D Assets Census in 2009" to estimate the software R&D expenses to be deducted in other years. Wang and Wang [3] believe that this approach essentially assumes that the intramural expenditure on R&D of software companies grows at the same rate as those of all companies. In light of this, at the provincial level, we assume that the growth rate of intramural expenditure on R&D of software companies is consistent with the growth rate of R&D expenditure of software companies. Based on the R&D expenditures of software companies in each province from 2007 to 2015 in the "China Electronics and Information Industry Statistical Yearbook (Software Volume)" and the intramural expenditures on R&D by expenditure purpose of software industry companies in 2009 from the "Compilation of the Second National R&D Assets Census in 2009", we estimate the intramural expenditures on R&D by expenditure purpose of software industry companies for other years from 2007 to 2015, and the proportions of the respective intramural expenditures on R&D in each province. The average proportions of each province from 2007 to 2011 are used as the deduction ratio for software R&D expenses in each province before 2007. Similarly, the average proportions from 2011 to 2015 are used as the deduction ratio for software R&D expenses in each province after 2015. Subsequently, deductions are made accordingly for each component of intramural expenditure on R&D in each province. For the high-tech industries in each province, we assume that their deduction ratio for software R&D expenses is the same as that of their respective provinces. The second step is to exclude the land value. Following the approach of Jiang and Sun [18], we reduce the asset expenditures by 5% annually.

2.1.2. R&D Asset Price Index

Drawing on the approach of Wang and Wang [3,4], we construct a Fisher-weighted R&D asset price index. Since R&D investment is derived from the intramural expenditure on R&D, this index aligns with the R&D capitalization accounting process and has optimal theoretical and empirical properties. Specifically, based on the composition of intramural expenditure on R&D by expenditure purpose, where labor cost corresponds to the R&D personnel wage index, other routine expenditures correspond to the industrial producer purchase price index, and asset expenditure corresponds to the fixed asset investment price index, the R&D asset price index can be obtained as follows:

$$P_{st}^{F} = \sqrt{P_{st}^{L} \times P_{st}^{P}} = \sqrt{\left(\sum_{m=1}^{3} \frac{p_{mt}}{p_{ms}} \times w_{ms}\right)\left(\frac{1}{\sum_{m=1}^{3} \frac{p_{ms}}{p_{mt}} \times w_{mt}}\right)}, \tag{3}$$

where P_{st}^{L} and P_{st}^{P}, respectively, represent the Laspeyres index and Paasche index, weighted by the quantities in base period s and current period t. p_{mt} represents the price of the mth component of intramural expenditure on R&D in period t, and w_{mt} represents the proportion of the mth component in the total expenditures in period t. To incorporate the structural information of intramural expenditure on R&D by expenditure purpose in each period, we calculate the R&D asset price index for adjacent years based on this method. To reflect changes in the wages of R&D personnel, we construct an R&D Labor Price Index (*LPI*) following the approaches of Jiang and Sun [18] and Zhu [6]:

$$LPI_t = \frac{L_{R\&D}(t)/Q(t)}{L_{R\&D}(t-1)/Q(t-1)}, \tag{4}$$

where $L_{R\&D}(t)$ is the value of labor cost in the intramural expenditure on R&D in period t, and $Q(t)$ is the full-time equivalent of R&D personnel in period t.

2.1.3. R&D Asset Depreciation Rate

We calculate the depreciation rate of R&D assets based on three types of R&D activities: basic research, applied research, and experimental development. Considering the progressively decreasing difficulty of breakthroughs from basic research, to applied research, and then to experimental development, we follow the approach of Hou and Chen [19], assuming service lives of 20 years, 15 years, and 10 years for these three types of R&D assets, respectively. We employ a geometric declining balance method with a residual value rate of 10% to calculate the depreciation rates separately. Then, we use the proportions of expenditures on basic research, applied research, and experimental development in the intramural expenditure on R&D as weights to calculate a weighted average of the depreciation rates, thereby obtaining the annual depreciation rates of R&D assets for each target entity.

2.1.4. Initial R&D Capital Stock

Most scholars follow the method proposed by Griliches [20], estimating the base period R&D capital stock under the assumption that "the growth rate of the R&D capital stock is equal to the growth rate of R&D investment". The rationale behind this assumption is that, in the long term, the growth rates of investment and capital stock are similar [18]; hence, we adopt the same assumption. Under this premise, the initial R&D capital stock can be calculated as follows:

$$RDK_{i0} = \frac{(1-\delta_{i1}/2)RDI_{i1}}{rdg_i + \delta_{i1}}, \tag{5}$$

where RDI_{i1} is the increase in actual R&D investment of target entity i in the first year, rdg_i is the growth rate of i's R&D capital stock, assumed to be equal to the growth rate of the actual R&D investment, and δ_{i1} is the depreciation rate of i's R&D assets in the first year, incorporating the average depreciation rate of R&D assets over the first five years, including the initial year, into the calculation. The growth rate of the actual R&D investment is estimated using the regression method of the BEA [21], starting with:

$$\ln RDI_{it} = b_i + m_i t + \varepsilon_{it}, \tag{6}$$

where t is the time variable, m_i is the coefficient of the time variable t, b_i is the constant term, and ε_{it} is the random error term. Following the method of Hou and Chen [19] for estimating m_i, the R&D investment growth rate can further be calculated as:

$$rdg_i = e^{m_i} - 1. \tag{7}$$

2.2. Measurement of Carbon Emissions

2.2.1. Estimation Method

This paper employs the carbon emission factor method to estimate carbon emissions at the provincial level in China. According to the "Provincial Greenhouse Gas Inventory Compilation Guidelines (Trial)", carbon emissions from cement production are generated during the production of the intermediate product, cement clinker. Therefore, carbon emissions from cement production need to be calculated based on the output of cement clinker. The formula for calculating carbon emissions from energy consumption and cement production is:

$$C = \sum_{i=1}^{n} CE_i + C_{cement} = \sum_{i=1}^{n} EC_i \times ECOE_i + Q \times CCOE, \quad (8)$$

where C represents the total carbon emissions, CE_i is the carbon emission from the consumption of the ith type of energy, C_{cement} is the carbon emission from cement production, EC_i is the consumption of the ith type of energy, $ECOE_i$ is the carbon emission coefficient of the ith type of energy, Q is the production of cement clinker, and $CCOE$ is the carbon emission coefficient for cement clinker. According to the 2006 IPCC Guidelines and the "Provincial Greenhouse Gas Inventory Compilation Guidelines (Trial)", the carbon emission coefficient for a specific type of energy equals its lower heating value multiplied by the carbon content per unit of energy and the oxidation rate, which is then multiplied by the atomic mass conversion factor 44/12.

2.2.2. Energy Consumption

The selection of energy types and the amount of energy consumed are key factors affecting the estimation of carbon emissions.

1. Selection of Energy Types

This paper follows two principles when selecting energy types. First is comprehensiveness. To ensure the completeness of the estimation results, as many types of energy as possible should be included in the estimation. Second is comparability; to ensure the cross-period comparability of carbon emission estimation results, the energy types selected during the estimation period should remain consistent. Since 2010, the Energy Balance in the "China Energy Statistical Yearbook" has added 10 types of energy, namely, Gangue, Blast Furnace Gas, Converter Gas, Naphtha, Lubricants, Paraffin Waxes, White Spirit, Bitumen Asphalt, Petroleum Coke, and Liquefied Natural Gas (LNG). Based on the principle of comparability, our estimation process does not include the 9 types of energy other than LNG. This is because LNG is essentially the same type of energy as natural gas, so we include it in natural gas during our estimations. When they are in standard quantities, they can be directly added together; when they are in physical quantities, LNG is divided by the conversion factor (0.45 t/m^3) before being added to natural gas, since the density of natural gas is 430 kg–470 kg/m^3, and 0.45 t/m^3 is its average value. Additionally, the proportion of "Other Energy" is very small and its carbon emission coefficient is difficult to calculate, so it is also not considered. "Heat" and "Electricity" do not produce carbon emissions if they are primary energy, and they are converted from other types of energy if they are secondary energy, and only the energy used to generate heat and electricity need to be considered. Therefore, based on the principle of comprehensiveness, this paper ultimately includes the following 17 types of energy in the calculation of carbon emissions from energy consumption: Raw Coal, Cleaned Coal, Other Washed Coal, Briquettes, Coke, Coke Oven Gas, Other Gas, Other Coking Products, Crude Oil, Gasoline, Kerosene, Diesel Oil, Fuel Oil, Liquefied Petroleum Gas, Refinery Dry Gas, Other Petroleum Products, and Natural Gas.

2. Energy Consumption Amounts

When calculating energy consumption amounts, we follow the principles of counting actual consumption and avoiding double counting. Based on this principle, we use the total final consumption from the regional energy balance sheets as a benchmark. The definition of total final consumption in the "China Energy Statistical Yearbook" refers to the amount of energy consumed by all sectors and residential living within a certain period across the nation (region), after deducting the amounts used for processing, converting into secondary energy consumption, and losses. Then, we add the energy consumption used for

"Thermal Power" and "Heating Supply" under "Input (−) & Output (+) of Transformation", and deduct the energy consumption used as raw materials that do not produce carbon emissions. This yields the energy consumption used to estimate carbon emissions in each province:

$$\text{Energy consumption that produces carbon emissions} = \text{Total final consumption} + \text{Input for electricity or heating} - \text{Energy input used as raw materials.} \tag{9}$$

The choice of carbon emission coefficients for energy sources also impacts the estimation results. Yang and Lahr [22], based on IPCC (Intergovernmental Panel on Climate Change) coefficients, calculated the adjusted emission coefficients for China, and we adopt their results (as shown in Table 1).

Table 1. Carbon emission coefficients for energy sources.

Energy Source	Carbon Emission Coefficient (Physical Quantity)	Carbon Emission Coefficient (Standard Quantity)
Raw Coal	1.978	2.769
Cleaned Coal	2.492	2.769
Other Washed Coal	0.791	2.769
Briquettes	1.825	2.555
Coke	3.042	3.132
Coke Oven Gas	7.42	1.299
Other Gas	2.32	1.299
Natural Gas	21.84	1.643
Crude Oil	3.065	2.146
Gasoline	2.985	2.029
Kerosene	3.097	2.105
Diesel Oil	3.167	2.169
Fuel Oil	3.237	2.266
Liquefied Petroleum Gas	3.1667	1.847
Refinery Gas	2.653	1.688
Other Petroleum Products	3.065	2.146
Other Coking Products	3.043	3.132

Notes: The units for standard quantities are "10,000 tons/10,000 tons"; except for the physical quantities of Coke Oven Gas, Other Gas, and Natural Gas, which are "10,000 tons/100 million cubic meters", the units for physical quantities of all other energy sources are "10,000 tons/10,000 tons".

2.2.3. Cement Production

Since the carbon emissions from cement production are generated during the production of the intermediate product, cement clinker, estimating the emissions from this process requires data on the output of cement clinker and its carbon emission coefficient.

According to the "China Cement Yearbook", "China Building Materials Industry Yearbook", and "China Economic Census Yearbook (Volume on Secondary Industry, Part One)", provincial data on cement clinker production are available only for the years 2005–2016 and 2018. Therefore, it is necessary to complete the missing data for other years for each province. Firstly, we complete the national-level data on cement clinker production. At the national level, there are cement clinker production data for 1990–1995, 1997, and 2001–2019, and cement production data for 1990–2019. We observe a clear linear relationship between national cement clinker production and cement production from 1990 to 2019, and estimate the parameters of the linear function using data from 1990–2002. The results indicate that the constant term is not significant, so we assume a proportional relationship between cement clinker production and cement production, and re-estimate the proportionality coefficient to complete the missing data on cement clinker production. Secondly, we complete the missing provincial data on cement clinker production. Assuming that a proportional relationship still exists between cement clinker production and cement production at the provincial level, we then distribute the national cement clinker production in the years with missing data according to the proportion of cement production in those provinces, thereby obtaining the completed historical provincial data on cement clinker production. According to the "Provincial Greenhouse Gas Inventory Compilation Guide (Trial)", the carbon emission coefficient for cement clinker is taken as 0.538 tons of carbon dioxide per ton of cement clinker.

2.3. Model Setting

There are numerous analytical models for the factors affecting carbon emissions, including the IPAT model [23], the Kaya identity [24], the STIRPAT model [25], and the LMDI decomposition model [26]. Each method differs in its applicability and assumptions. The IPAT model and Kaya identity are suitable for year-by-year or periodical analysis, constrained by the necessity of equivalence, and inherently assume that the impact of each influencing factor on carbon emissions is proportional, making it difficult to analyze the impact of a single factor. Although the LMDI decomposition model can quantify the contribution rate of each influencing factor in a specific year, it cannot examine the change in carbon dioxide caused by the change of a certain factor. The STIRPAT model compensates for the shortcomings of these models and can measure the impacts of various influencing factors. However, the traditional STIRPAT model only includes three factors: population size, economic growth level, and technological variables, which cannot comprehensively describe the impacts of economic and social factors on carbon emissions. Therefore, this paper expands on the basis of the Kaya identity to improve the STIRPAT model. According to the Kaya identity, carbon emissions can be decomposed as follows:

$$E = P \times \frac{Y}{P} \times EI \times ES \times other, \tag{10}$$

where E represents the carbon emissions of each province, P is the population size of each province, Y is the output level, EI is the energy intensity, which is the amount of energy consumption measured in standard coal divided by the output level, ES is the energy consumption structure, which is the proportion of raw coal converted into standard coal in the total energy consumption, and $other$ represents other variables.

Existing studies have shown that factors such as population size [25], economic growth level [25], R&D activities [7–13], industrial structure [27,28], environmental policies [29–31], energy intensity [10,32], energy consumption structure [10,32], urbanization level [33], foreign direct investment (FDI) [10], and human capital level (average years of education) [34] all affect carbon emissions. R&D activities, including basic research, applied research, and experimental development, cover a broad range and thus need to be considered from two dimensions: the quantity and the quality of R&D activities. Companies, aiming for profit and efficiency, tend to engage in R&D activities that are short in cycle, quick to show results, and closely related to production activities. Considering that technological innovation is the most crucial feature of high-tech industries, this paper includes not only the R&D capital stock, an indicator representing the quantity of R&D activities, but also the proportion of R&D capital stock in high-tech industries, which represents the quality of R&D activities, into the model. Based on the aforementioned factors affecting carbon emissions, we integrate and refine the Kaya identity and the STIRPAT model to construct the following model:

$$E_{it} = \alpha_0 + X\alpha + v_t + \lambda_i + \varepsilon_{it}, \tag{11}$$

where E represents the carbon emissions of each province, i denotes the province, t denotes the year, and X represents explanatory or control variables; α_0 is the constant term, v_t is the time effect, λ_i is the individual effect, and ε_{it} is the random error term. To eliminate heteroscedasticity and ensure the stability of the series, we take the logarithm of some variables.

2.4. Variable Definitions and Data Sources

This paper takes the carbon emissions of each province as the dependent variable, and variables such as population size, economic growth level, R&D capital stock, the proportion of R&D capital stock in high-tech industries, industrial structure upgrading, environmental policies, energy intensity, energy consumption structure, urbanization level, foreign direct investment, and average years of education as explanatory or control variables. The definitions of the variables are as follows:

1. Carbon emissions—Measured by the carbon emission results obtained in Section 2.2, and the natural logarithm is taken;
2. Population size—Measured by the end-of-year population size of each province, and the natural logarithm is taken;
3. Economic growth level—Measured by per capita value added, and the natural logarithm is taken. The Environmental Kuznets Curve describes the "inverted U-shaped" relationship between environmental quality and economic growth level. It suggests that environmental quality tends to deteriorate initially and then improve as economic growth level rises. Essentially, the curve represents a regularity of growing first and cleaning up later [35]. Numerous studies support the existence of the Environmental Kuznets Curve [36–38];
4. R&D Capital Stock—This indicator represents the quantity of R&D activities. It is measured by the R&D capital stock of each province calculated in Section 2.1, and the natural logarithm is taken. Since the intramural expenditures on R&D by expenditure purpose in China's provinces have only been published since 2009, we estimate the missing data before 2009 following the approach of Hou and Chen [19];
5. Proportion of R&D capital stock in high-tech industries—This indicator represents the quality of R&D activities. It is measured by dividing the R&D capital stock of high-tech industries calculated in this paper by the total R&D capital stock of each province. Since the "China High-Tech Industry Statistical Yearbook" began publishing the composition items of intramural expenditure on R&D by expenditure purpose for high-tech industries in each province from 2009, we estimate the missing data before 2009;
6. Industrial structure upgrading—Following the approach of Fu [39], we calculate this indicator based on the spatial vector angle weighted value, which depicts the trend of the industrial structure evolving with the GDP structure of the three industries rising in the order of the primary, secondary, and tertiary sectors;
7. Environmental policy—Measured by the proportion of national investment in forestry completed since the beginning of the year to the regional GDP of the same period. Governmental investment on forestry reflects the government's emphasis on forestry. Forestry plays a crucial role in ecological civilization construction and has a unique function in climate change mitigation, mainly reflected in forests' ability to absorb CO_2. Indirect emission reduction through forestry has been incorporated into international rules and has become a common practice internationally;
8. Energy intensity—Measured by the total energy consumption divided by the regional GDP;
9. Energy consumption structure—Measured by the proportion of raw coal converted to standard coal in the total energy consumption. The mix of energy sources with different cleanliness levels affects the carbon emissions from energy consumption. China's energy endowment structure of "rich in coal, poor in oil, and scarce in gas" determines that its energy consumption structure is dominated by raw coal;
10. Urbanization level—Measured by the proportion of urban population in the total permanent resident population at the end of the year in each province;
11. Foreign direct investment (FDI)—Measured by the natural logarithm of foreign direct investment. FDI brings not only capital but also technology to China, reducing carbon emission pressure through technological spillovers;
12. Average years of education—Following the approach of Wang [40], this indicator is calculated based on the average years of education for the population aged 6 years and above. The average years of education can reflect the level of human capital in each province, and to some extent, the overall quality of the public, including envi-

ronmental awareness. China incorporates the cultivation of environmental protection awareness into the entire education process, suggesting that the longer the average years of education in a province, the stronger the public awareness of environmental protection.

Our research sample consists of panel data from 30 provincial administrative regions in China, spanning from 2000 to 2019. The following data were excluded from our sample: (1) Data from Hong Kong, Macau, Taiwan, and Tibet, due to the unavailability of relevant data. (2) Data for Ningxia from 2000 to 2002 and for Hainan in 2002, as their energy consumption data were not disclosed by Chinese authorities. (3) Data for Xinjiang in 2000 related to the variable "Proportion of R&D Capital Stock in High-Tech Industries", because the corresponding intramural expenditure on R&D was not disclosed. (4) Data from 2000 to 2010 for the variable "Environmental Policy", because the proportion of national investment in forestry was not disclosed until 2011. We chose 2019 as the cut-off year to exclude the impact of the subsequent pandemic. The data mainly come from the "China Science and Technology Statistical Yearbook", "China Statistical Yearbook", "China Fixed Assets Investment Statistical Yearbook", "China High-Tech Industry Statistical Yearbook", "China Energy Statistical Yearbook", "China Forestry Statistical Yearbook", and provincial statistical yearbooks. To eliminate the impacts of price factors from different periods, value indicators are all converted into constant prices of the year 2000 using price indices. Table 2 shows the symbols and descriptive statistics of the variables.

Table 2. Variable symbols and descriptive statistics.

Variables	Symbols	Obs.	Mean	Std. Dev.	Min.	Max.
Carbon Emissions (10^4 tons)	*E*	596	9.912	0.815	6.855	11.465
Population Size (10^4 people)	*P*	620	8.083	0.861	5.553	9.352
Economic Growth Level (CNY)	*pgdp*	620	9.156	0.535	7.887	10.784
R&D Capital Stock (10^4 CNY)	*RD*	620	14.161	1.681	8.625	17.648
Proportion of R&D Capital Stock in High-Tech Industries	*hRD_share*	610	0.114	0.090	0.000 [1]	0.475
Industrial Structure Upgrading	*ind_stru*	620	6.556	0.324	5.925	7.654
Environmental Policy (%)	*grpolicypub*	279	0.448	0.486	0.005	3.171
Energy Intensity (tce/10^4 CNY)	*EI*	596	2.747	2.017	0.577	17.737
Energy Consumption Structure (proportion)	*ES*	596	0.610	0.133	0.022	0.911
Urbanization Level (proportion)	*urban*	620	0.503	0.158	0.191	0.942
Foreign Direct Investment (10^8 CNY)	*FDI*	600	3.869	1.654	−3.121	6.921
Average Years of Education (years)	*edu_year*	620	8.483	1.26	3.43	12.681

[1] The actual value is approximately 0.0002803.

3. Results

In our empirical analysis, the provincial panel data used are characterized by a large N and small T (a short panel); hence, the standard panel model is our first choice for regression analysis. However, after testing, we found that the fixed effects model suffers from severe heteroscedasticity, serial correlation, and cross-sectional dependence issues. Therefore, we chose to use the Panel-Corrected Standard Error (PCSE) method and control for time effects. Table 3 reports the model's estimation results.

Column (1) of Table 3 presents the baseline regression results, setting the time span to 2011–2019 due to the environmental policy variable covering the years 2011–2019. Column (2) shows regression results that include only the R&D capital stock, excluding the proportion of R&D capital stock in high-tech industries. Column (3) includes only the proportion of R&D capital stock in high-tech industries, excluding the R&D capital stock. Column (4) shows regression results after expanding the sample size, where the model does not include environmental policy, and the time span is set to 2000–2019. Column (5) shows regression results that add a quadratic term of economic growth level to the baseline model of column (1), to test for the existence of an Environmental Kuznets Curve. Column (6) shows regression results that further include an interaction term between economic growth level and environmental policy based on column (5), to test the impact of environmental policy on the turning point of the Environmental Kuznets Curve.

Table 3. Model estimation results.

Variables	(1) Baseline Regression	(2) R&D Quantity Only	(3) R&D Quality Only	(4) Expand Sample Size	(5) Include Quadratic Terms	(6) Include Interaction Terms
P	1.024 *** (35.90)	1.037 *** (29.31)	1.060 *** (54.88)	1.043 *** (44.98)	1.048 *** (39.85)	1.006 *** (35.70)
pgdp	0.424 *** (15.69)	0.429 *** (14.47)	0.439 *** (18.07)	0.444 *** (13.45)	4.088 *** (11.48)	5.010 *** (12.72)
pgdp×*pgdp*					−0.195 *** (−10.47)	−0.239 *** (−11.81)
pgdp×*grpolicypub*						−0.334 *** (−4.15)
RD	0.027 (1.49)	0.022 (0.97)		0.005 (0.21)	0.008 (0.52)	0.019 (1.20)
hRD_share	−0.569 *** (−6.83)		−0.565 *** (−6.73)	−0.387 *** (−6.02)	−0.597 *** (−7.39)	−0.676 *** (−8.38)
ind_stru	−0.324 *** (−7.18)	−0.376 *** (−7.95)	−0.301 *** (−7.79)	−0.098 (−1.41)	−0.090 ** (−2.20)	−0.048 (−1.06)
grpolicypub	−0.170 *** (−4.69)	−0.144 *** (−3.88)	−0.169 *** (−4.69)		−0.127 *** (−3.47)	2.984 *** (3.97)
EI	0.156 *** (13.55)	0.161 *** (13.65)	0.155 *** (14.12)	0.182 *** (13.09)	0.151 *** (13.91)	0.153 *** (13.40)
ES	0.652 *** (8.20)	0.605 *** (6.97)	0.657 *** (8.65)	0.723 *** (7.60)	0.572 *** (7.50)	0.487 *** (5.40)
urban	1.340 *** (6.18)	1.325 *** (5.54)	1.444 *** (6.75)	1.361 *** (6.60)	1.170 *** (5.72)	0.558 ** (2.43)
FDI	−0.042 *** (−3.56)	−0.050 *** (−4.23)	−0.041 *** (−3.50)	−0.022 *** (−4.24)	−0.042 *** (−3.95)	−0.023 ** (−2.00)
edu_year	−0.093 *** (−6.57)	−0.067 *** (−5.26)	−0.094 *** (−6.83)	−0.059 *** (−4.04)	−0.070 *** (−4.86)	−0.013 (−0.73)
Constant	−0.876 *** (−2.97)	−0.854 *** (−2.65)	−1.110 *** (−4.93)	−3.450 *** (−7.07)	−19.532 *** (−11.35)	−24.640 *** (−12.25)
N	270	270	270	595	270	270
R^2	0.946	0.942	0.945	0.941	0.949	0.952

Notes: The values in parentheses are t-values; ** and ***, respectively, indicate significance at the 5% and 1% levels.

Table 3 shows that the coefficients, signs, and significance of the explanatory variables in the models remain essentially stable, proving the robustness of the baseline regression results. The baseline regression results indicate that the impact of R&D capital stock on carbon emissions is not significant, while the proportion of R&D capital stock in high-tech industries has a significant negative effect on carbon emissions. For other explanatory variables, our findings align with those in the related literature [10,28,34]. Industrial structure upgrading, environmental policy, FDI, and average years of education all have significant negative effects on carbon emissions; whereas population size, economic growth level, energy intensity, energy consumption structure, and urbanization level all have significant positive effects on carbon emissions. After including the quadratic term of economic growth level, the coefficient of economic growth level is significantly positive, and the coefficient of its quadratic term is significantly negative, indicating the existence of an inverted U-shaped Environmental Kuznets Curve relationship between carbon emissions and economic growth level, i.e., environmental problems caused by carbon emissions tend to improve with higher levels of economic growth. After including the interaction term between environmental policy and economic growth level, the coefficient of this interaction term is significantly negative, indicating that environmental policy leads to an earlier appearance of the turning point in the inverted U-shaped curve of carbon emissions.

4. Discussion

4.1. Regional Heterogeneity Analysis

We further examine the carbon emission reduction effects of the quantity and quality of R&D activities in different regions. Based on the per capita value-added indicator and the marketization index of each province in 2019, we categorize provinces into regions with high or low levels of economic growth, and into regions with high or low levels of marketization. Table 4 reports the model's estimation results.

Table 4. Results of regional heterogeneity analysis.

Variables	Baseline Regression	Economic Growth Level		Marketization Level	
		High	Low	High	Low
P	1.024 ***	0.815 ***	1.298 ***	1.094 ***	1.309 ***
	(35.90)	(13.93)	(15.46)	(19.36)	(19.97)
pgdp	0.424 ***	0.367 ***	0.962 ***	0.750 ***	1.071 ***
	(15.69)	(5.82)	(8.68)	(21.98)	(11.06)
RD	0.027	0.256 ***	−0.083	−0.018	−0.078 ***
	(1.49)	(4.33)	(−1.57)	(−0.76)	(−3.34)
hRD_share	−0.569 ***	−0.972 ***	0.580 *	−0.419 ***	0.768 **
	(−6.83)	(−11.11)	(1.83)	(−4.98)	(2.24)
ind_stru	−0.324 ***	−1.059 ***	0.517 ***	−0.423 ***	0.666 ***
	(−7.18)	(−10.26)	(4.17)	(−6.62)	(5.08)
grpolicypub	−0.170 ***	−0.228 *	0.199 ***	−0.160 **	0.156 ***
	(−4.69)	(−1.93)	(2.92)	(−2.41)	(2.69)
EI	0.156 ***	0.161 ***	0.154 ***	0.376 ***	0.134 ***
	(13.55)	(11.93)	(16.92)	(18.20)	(19.15)
ES	0.652 ***	0.221	0.532 ***	0.330 ***	0.562 ***
	(8.20)	(1.01)	(6.74)	(7.94)	(4.14)
urban	1.340 ***	1.994 ***	0.924 *	1.062 ***	0.911 **
	(6.18)	(5.93)	(1.70)	(3.54)	(2.16)
FDI	−0.042 ***	−0.005	−0.056 ***	0.009	−0.069 ***
	(−3.56)	(−0.16)	(−3.67)	(0.47)	(−4.22)
edu_year	−0.093 ***	−0.159 ***	0.004	−0.129 ***	−0.024
	(−6.57)	(−2.98)	(0.14)	(−6.54)	(−1.09)
Constant	−0.876 ***	3.130 ***	−12.558 ***	−3.299 ***	−14.299 ***
	(−2.97)	(3.46)	(−6.60)	(−6.39)	(−7.73)
N	270	135	135	135	135
R^2	0.946	0.966	0.967	0.989	0.970

Notes: The values in parentheses are t-values; *, **, and ***, respectively, indicate significance at the 10%, 5%, and 1% levels.

From the perspective of economic growth level, the proportion of R&D capital stock in high-tech industries has a significantly negative effect on carbon emissions in regions with high economic levels, with an estimated parameter value of −0.972, compared to the national overall estimate of −0.569. This indicates that the carbon emission reduction effect of the proportion of R&D capital stock in high-tech industries is stronger than the national average in regions with high economic levels. The R&D capital stock in regions with high economic levels has a significant positive effect on carbon emissions, while in regions with low economic levels, the R&D capital stock's effect on carbon emissions is not significant. This may be because the increase in R&D capital stock in high-economic-level regions enhances their economic growth levels, which has a significant positive effect on carbon emissions, resulting in a significant positive value in the parameter estimates. Furthermore, the regression coefficients of industrial structure upgrading and environmental policy are significantly negative in regions with high economic growth levels, while they are significantly positive in regions with low economic growth levels.

From the perspective of marketization level, the proportion of R&D capital stock in high-tech industries has a significantly negative effect on carbon emissions in regions with high marketization levels, with an estimated parameter value of −0.419, making its carbon reduction effect slightly weaker than the national average. The R&D capital stock's effect on carbon emissions is not significant in regions with high marketization levels, while in regions with low marketization, the R&D capital stock has a significant negative effect on carbon emissions. Additionally, the regression coefficients of industrial structure upgrading and environmental policy are significantly negative in regions with high marketization levels and significantly positive in regions with low marketization levels.

The above results indicate that, in regions with high levels of economic growth and marketization, the carbon emission reduction effect of the proportion of R&D capital stock in high-tech industries is stronger.

4.2. Evolutionary Analysis

We further explore the evolutionary characteristics of the carbon emission reduction effects of the quantity and quality of R&D activities across provinces. We conduct a rolling regression on the model with a time span of 15 years. Since the time span of the environmental policy variable is from 2011 to 2019, which does not meet the requirements for evolutionary analysis, the environmental policy variable is not included in the evolutionary analysis. Table 5 reports the model's estimation results.

Table 5. Results of evolutionary analysis.

Variables	2000–2014	2001–2015	2002–2016	2003–2017	2004–2018	2005–2019
P	0.969 ***	0.961 ***	0.949 ***	0.967 ***	0.985 ***	1.033 ***
	(55.49)	(53.64)	(50.27)	(41.95)	(36.70)	(36.06)
pgdp	0.497 ***	0.494 ***	0.484 ***	0.491 ***	0.498 ***	0.503 ***
	(11.04)	(12.37)	(13.41)	(15.43)	(17.30)	(17.32)
RD	0.075 ***	0.082 ***	0.086 ***	0.074 ***	0.055 **	0.016
	(3.95)	(4.50)	(4.95)	(3.81)	(2.47)	(0.68)
hRD_share	−0.265 ***	−0.241 ***	−0.222 ***	−0.251 ***	−0.288 ***	−0.460 ***
	(−4.10)	(−3.58)	(−3.09)	(−3.60)	(−4.52)	(−6.31)
ind_stru	−0.245 ***	−0.280 ***	−0.308 ***	−0.292 ***	−0.271 ***	−0.239 ***
	(−3.71)	(−4.70)	(−5.82)	(−5.26)	(−4.86)	(−4.46)
EI	0.275 ***	0.262 ***	0.249 ***	0.224 ***	0.202 ***	0.167 ***
	(19.93)	(19.17)	(18.53)	(15.74)	(14.71)	(13.07)
ES	0.344 ***	0.337 ***	0.377 ***	0.482 ***	0.604 ***	0.801 ***
	(4.92)	(5.14)	(5.92)	(6.53)	(7.52)	(8.12)
urban	0.947 ***	0.915 ***	0.918 ***	0.953 ***	0.966 ***	1.156 ***
	(5.22)	(5.25)	(5.11)	(5.07)	(4.95)	(5.36)
FDI	−0.008	−0.010 *	−0.008	−0.015 **	−0.016 **	−0.020 ***
	(−1.54)	(−1.87)	(−1.39)	(−2.33)	(−2.51)	(−3.19)
edu_year	−0.037 ***	−0.043 ***	−0.053 ***	−0.062 ***	−0.064 ***	−0.068 ***
	(−2.70)	(−3.19)	(−3.85)	(−4.59)	(−4.91)	(−4.95)
Constant	−3.275 ***	−2.923 ***	−2.511 ***	−2.516 ***	−2.588 ***	−2.706 ***
	(−5.99)	(−5.53)	(−5.01)	(−5.09)	(−5.21)	(−5.43)
N	445	447	448	450	450	450
R^2	0.960	0.959	0.959	0.955	0.952	0.945

Notes: The values in parentheses are t-values; *, **, and ***, respectively, indicate significance at the 10%, 5%, and 1% levels.

The carbon emission reduction effect of the proportion of R&D capital stock in high-tech industries generally shows a trend of gradual strengthening. During the 2000–2014 period, the regression coefficient was −0.265, which increased to −0.460 in the 2005–2019 period. The promoting effect of R&D capital stock on carbon emissions changed from significant to insignificant, and showed a trend of weakening; the regression coefficient decreased from 0.075 in the 2000–2014 period to 0.016 in the 2005–2019 period, and became insignificant. Industrial structure upgrading has a significant negative impact on carbon emissions, and this impact fluctuates around a certain level. The carbon emission reduction effect of FDI changed from insignificant to significant and strengthened over time, with the regression coefficient moving from −0.008 (insignificant) in the 2000–2014 period to −0.020 in the 2005–2019 period. The carbon emission reduction effect of average years of education showed a trend of gradual strengthening, with the regression coefficient increasing from

−0.037 in the 2000–2014 period to −0.068 in the 2005–2019 period. The remaining variables all promote carbon emissions, among which the impacts of population size, economic growth level, energy consumption structure, and urbanization level generally show a trend of strengthening, while the impact of energy intensity shows a trend of weakening.

4.3. Influence Mechanism Analysis

In this section, we examine the mechanisms through which R&D activities influence carbon emissions. We establish the following mediation model based on the "R&D activities–industrial structure upgrading–carbon emissions" pathway:

$$E_{it} = \beta_{01} + R\beta_{21} + Z\beta_{31} + v_{1t} + \lambda_{1i} + \varepsilon_{1it}, \tag{12}$$

$$ind\_stru_{it} = \beta_{02} + R\beta_{22} + Z\beta_{32} + v_{2t} + \lambda_{2i} + \varepsilon_{2it}, \tag{13}$$

$$E_{it} = \beta_{03} + \beta_{13} ind\_stru_{it} + R\beta_{23} + Z\beta_{33} + v_{3t} + \lambda_{3i} + \varepsilon_{3it}, \tag{14}$$

where E represents carbon emissions, i denotes the province, t denotes the year, *ind_stru* is the level of industrial structure upgrading, R represents R&D capital stock (*RD*) and the proportion of R&D capital stock in high-tech industries (*hRD_share*), Z represents other variables such as population size, economic growth level, energy intensity, energy consumption structure, etc., β represents the estimated coefficient for constant terms or variables, v is the time effect, λ is the individual effect, and ε is the random error. We use the Panel-Corrected Standard Error method for estimation and control for time effects. Table 6 reports the model's estimation results.

Table 6. Results of influence mechanism analysis.

Variables	**(1)**	**(2)**	**(3)**
	E	***ind_stru***	***E***
P	1.075 ***	−0.158 ***	1.024 ***
	(33.97)	(−10.31)	(35.90)
pgdp	0.385 ***	0.120 ***	0.424 ***
	(11.87)	(4.87)	(15.69)
RD	−0.025	0.160 ***	0.027
	(−1.53)	(19.45)	(1.49)
hRD_share	−0.658 ***	0.274 **	−0.569 ***
	(−7.20)	(2.52)	(−6.83)
ind_stru			−0.324 ***
			(−7.18)
grpolicypub	−0.175 ***	0.014	−0.170 ***
	(−4.38)	(0.35)	(−4.69)
EI	0.154 ***	0.007 **	0.156 ***
	(14.41)	(2.47)	(13.55)
ES	0.732 ***	−0.248 ***	0.652 ***
	(10.62)	(−4.36)	(8.20)
urban	1.261 ***	0.244	1.340 ***
	(4.98)	(1.44)	(6.18)
FDI	−0.029 **	−0.040 ***	−0.042 ***
	(−2.35)	(−4.69)	(−3.56)
edu_year	−0.107 ***	0.045 ***	−0.093 ***
	(−8.19)	(4.76)	(−6.57)
Constant	−2.198 ***	4.080 ***	−0.876 ***
	(−9.28)	(21.90)	(−2.97)
N	270	270	270
R^2	0.942	0.833	0.946

Notes: The values in parentheses are t-values; ** and ***, respectively, indicate significance at the 5% and 1% levels.

The coefficients for the total effect and the direct effect of R&D capital stock on carbon emissions are −0.025 and 0.027, respectively, both of which are not significant. R&D capital stock has a significant positive effect on industrial structure upgrading, with a coefficient of 0.160, while industrial structure upgrading has a significant negative effect on carbon emissions, with a coefficient of −0.324. This indicates that R&D capital stock has a significant indirect negative effect on carbon emissions through industrial structure upgrading, with this indirect effect being −0.0518. Since the total effect of R&D capital stock on carbon emissions is not significant, it should be considered a masking effect, meaning that the total effect is concealed. A possible explanation is that R&D capital stock has a negative effect on carbon emissions through industrial structure upgrading on one hand and a positive effect through other variables on the other hand. For example, R&D capital stock has a positive effect on economic growth level, which in turn has a positive effect on carbon emissions; thus, R&D capital stock exerts a positive effect on carbon emissions through economic growth level. In this way, the negative and positive effects offset each other, making the total effect of R&D capital stock on carbon emissions non-significant.

The coefficients for the total effect and the direct effect of the proportion of R&D capital stock in high-tech industries on carbon emissions are −0.658 and −0.569, respectively, both of which are significant. The proportion of R&D capital stock in high-tech industries has a significant positive effect on industrial structure upgrading, with a coefficient of 0.274, and industrial structure upgrading has a significant negative effect on carbon emissions, with a coefficient of −0.324. Therefore, R&D capital stock exerts a significant negative effect on carbon emissions through industrial structure upgrading, with this indirect effect being approximately −0.0888. Since the total effect, indirect effect, and direct effect of the proportion of R&D capital stock in high-tech industries on carbon emissions are all significant, it should be considered a partial mediation effect, meaning the mediation effect of the proportion of R&D capital stock in high-tech industries on carbon emissions accounts for about 13.49% of the total effect.

5. Conclusions

This paper analyzes the carbon emission reduction effects of the quality and quantity of R&D activities, with the main findings as follows:

1. The primary regression analysis shows that the quality of R&D activities has a negative impact on carbon emissions, while the quantity of R&D activities does not have a significant impact. From the perspective of other variables, industrial structure upgrading, environmental policy, FDI, and the average years of education all have negative effects on carbon emissions, whereas population size, economic growth level, energy intensity, energy consumption structure, and urbanization level all have positive effects on carbon emissions. Furthermore, there exists an inverted U-shaped Environmental Kuznets Curve relationship between carbon emissions and economic growth level. The government's implementation of environmental policies initiates the turning point in the inverted U-shaped curve of carbon emissions to appear earlier;
2. Regional heterogeneity analysis shows that, from the perspective of economic growth level, only in regions with high economic growth does the quality of R&D activities have a negative effect on carbon emissions, while the quantity of R&D activities has a positive effect. From the perspective of marketization level, only in regions with high marketization levels does the quality of R&D activities have a negative effect on carbon emissions, while the quantity of R&D activities does not have a significant effect. Moreover, the coefficients of industrial structure upgrading and environmental policy are significantly negative in regions with high levels of economic growth and marketization, while being significantly positive in regions with low levels of economic growth and marketization;
3. Evolutionary analysis shows that the carbon emission reduction effect of the quality of R&D activities tends to strengthen over time, while the positive effect of the quantity of R&D activities on carbon emissions shifts from significant to insignificant, and

shows a weakening trend over time. Industrial structure upgrading has a significant negative effect on carbon emissions. The carbon emission reduction effects of FDI and average years of education show a strengthening trend over time;
4. Influence mechanism analysis shows that both the quality and quantity of R&D activities reduce carbon emissions by promoting industrial structure upgrading.

Based on the findings of this paper, to reduce carbon emissions more effectively, firstly, relevant departments should consider both the quantity and quality of R&D and adopt a multi-faceted approach to promote industrial structure upgrading, enact appropriate environmental policies, expand the level of opening up, and value education, among other measures. Secondly, relevant departments should focus on improving the level of economic growth, pursue high-quality development, and further advance marketization reforms to fully leverage the market's decisive role in resource allocation. Finally, relevant departments should continually improve the fiscal and financial service systems that support innovation, reducing carbon emissions through promoting technological innovation. On one hand, a collaborative innovation mechanism involving industry, academia, research, and application can be established to accelerate the transformation and industrialization of scientific and technological achievements; on the other hand, the intellectual property protection system can be improved to provide guarantees for enterprises engaging in technological innovation.

The primary limitation of this paper is that it does not incorporate spatial factors into the analytical framework. This is because the Moran's I indices calculated using spatial weight matrices such as adjacency and economic distance matrices for carbon emissions in Chinese provinces are not significant, indicating a lack of significant spatial correlation in carbon emissions among the provinces. In future research, we plan to explore additional data sources and develop spatial weight matrices tailored to our study's needs, to further investigate the spatial correlations of carbon emissions.

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