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Is There Any Difference in the Effect of Different R and D Sources on Carbon Intensity in China?

Feng Feng and Linlin Peng *

School of Management, University of Science and Technology of China, Hefei 230026, China; ffeng@ustc.edu.cn
* Correspondence: linlinscu@163.com

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Abstract: In recent decades, climate change, mostly caused by CO_2 emissions, has become a critical issue of concern to people worldwide. It is necessary for countries all around the world to reduce carbon emissions. China, as the world's largest carbon emitter, is under great pressure to implement carbon-reduction strategies. Technological progress plays a crucial role in balancing environmental and economic development. The main objective of this work is to empirically compare the effects of government and enterprise research and development (R and D) on carbon-emission reduction using the panel data of 30 Chinese provinces from 2009 to 2016. The effects of both government and enterprise R and D investment on carbon intensity are compared in detail through a linear model and a threshold-regression model. Linear-regression results shows that both government and enterprise R and D decrease carbon intensity, while enterprise investment tends to be more instant. Further threshold-regression results indicate that the effects of government and enterprise R and D on carbon intensity are different in different urbanization stages. Guiding enterprises to invest in R and D in medium-developing areas, and increasing government support and subsidies for R and D activities in underdeveloped areas should be an important goal of the government policies.

Keywords: carbon intensity; R and D; threshold model

1. Introduction

Global warming has become one of the most severe global problems. It is caused by the increase in atmospheric greenhouse gases, most notably CO_2, which mainly comes from the burning of fossil fuel [1]. The problems caused by CO_2 emissions are becoming increasingly serious [2]. Controlling carbon emissions has now become a global political, economic, and social issue. To avoid threats from global warming, the international community and numerous countries are making emission-reduction efforts. The European Union (EU) has been running a carbon market in 31 countries since 2005. The EU Emissions Trading Scheme (EU ETS), as the first, largest, and most prominent system for regulating carbon emissions in the European Union, has reduced CO_2 emissions and increased low-carbon innovation [3,4]. With the rapid growth of CO_2 emissions, China overtook the United States as the world's largest CO_2 emitter in 2006. This trend has placed enormous international pressure on China [5]. It is vital for China to implement more efficient carbon-emission reduction strategies [6,7]. China put forward a quantitative goal to control greenhouse-gas emissions in 2009. In 2011, China's Twelfth Five-Year Plan stated that carbon intensity must be decreased by 17%, along with a 16% decrease in energy consumption during this time period. In 2015, China confirmed the goal that CO_2 emissions would peak around 2030, and that they would strive to reach this goal as early as possible. Therefore, under this ambitious goal, the question arises of how to achieve low-carbon development under China's realistic national conditions.

Numerous studies have been conducted to investigate carbon emissions in China, as well as to identify their influencing factors [8–12]. There is always a dilemma between economic development and environmental protection. Economic growth, which is based on the consumption of fossil fuels, is closely related to environmental degradation [13]. Scholars have come to the consensus that innovation plays a critical role in decreasing carbon emissions. The mechanism to achieve the balance between development and environment is technological progress. Gerlagh claimed that the value of technological progress is reflected in two aspects [14]. On the one hand, carbon prices are lowered, which reduces the burden of mandatory emission reduction. On the other hand, carbon reductions under technological progress may generate learning benefits, thereby reducing cost. Wei and Yang researched the influence of technological progress on CO_2 and indicated that R and D and the introduction of new technologies contributed to carbon-emissions reductions [15]. Some other studies also indicated that economic development and technological progress were the most crucial factors influencing CO_2 emissions [16–18]. In conclusion, technological progress plays a key role in promoting less pollution and more sustainable economic activities.

For an open economic subject, there are two main sources of technological progress, technological innovation and technological introduction. Technological innovation comes from domestic R and D activities. Technology introduction is mainly achieved through two methods, one is the direct introduction of foreign advanced technology, and the other is the indirect introduction of advanced technology through foreign direct investment (FDI) and international trade channels. Empirical studies were conducted to examine the relationship between technology introduction and carbon emissions. The introduction of management and advanced technologies in host countries is considered to be conducive to a better environment [19]. Sun et al. examined the effect of FDI and trade openness on carbon emissions through the autoregressive distributed lag (ARDL) model, the findings of which indicated that both FDI and trade promoted carbon-emission reduction [20]. The results also validate the important role of technological advances in curbing carbon emissions. Similarly, technological innovation could not only promote economic growth, but also lead to activities and products that are more efficient and less polluting. Sun et al. proposed that every technological innovation plays a powerful role in carbon-emission reduction [21]. Technology innovation is mainly achieved through domestic R and D investment. Similar papers regard R and D as a measure of technology innovation. The question attracting the attention of scholars is whether R and D can be regarded as a driver of less-polluting economic growth. Previous studies proved that R and D spending in the energy sector is beneficial to carbon-emission abatement. However, in addition to the energy sector, the innovation process and carbon emissions involve many other economic sectors. Improving the environment is a major issue that needs the participation of all economic sectors. Therefore, when analyzing the factors influencing carbon emissions, it is also necessary to take the effect of aggregate R and D into consideration. To fill this gap, Fernández et al. examined the influence that aggregate R and D spending can have in reducing the level of carbon emissions, and therefore achieving sustainable growth [13]. Results reveals that aggregate R and D involving all economic sectors is favorable in carbon-emission reduction. R and D activities present both direct and indirect beneficial influences on the environment. From a direct perspective, R and D motivates the production of green products and incentivizes high-efficiency technology, which helps mitigate carbon emissions. In an indirect perspective, R and D plays a crucial role in promoting the optimization of industrial structures. Thus, no matter whether R and D spending is on a specific sector or aggregate, the result that R and D is a key factor in improving the environment is consistent.

There are two main sources for R and D in China, government R and D investment and enterprise R and D investment. In 2006, the Chinese government put forward the strategic goal of establishing the main position of enterprise technology innovation. However, in addition to the mainstream view of promoting the enterprise as the subject, there are also many other opinions, such as entrepreneurial and pluralistic subjects. In 2015, the Chinese State Council proposed the establishment of a national innovation system based on enterprises, and realized the main position of enterprise R and D investment and technological innovation. In recent years, enterprise R and D expenditures have rapidly increased; although the total amount is still growing, the proportion of government R and D has tended to decrease [22]. Driven by a series of national policies, enterprise R and D expenditures in almost all regions have accounted for more than 50% of the total. In this case, can the establishment of an enterprise R and D subject be maximized to reduce carbon emissions in different regions? Is there any distinction in the effect of different R and D subjects on carbon emissions in China? Since the development gap between different regions in China is very large, should there be a difference in the establishment of R and D input subjects at different levels of development to maximize carbon-emission reduction? Although carbon emissions have been widely studied, the above questions remain to be further explored. There is still no comparative research on the differences between different sources of R and D. This is the motivation for this research. The final object of this paper is to find the optimal R and D subject to minimize emissions for areas at different development levels.

Since carbon intensity (calculated as the ratio of CO_2 emissions to GDP) is one of the most important indexes and is used to control for CO_2 emissions [23,24], it is of vital significance to evaluate the relationship between R and D investment subjects and carbon intensity in China. This paper aims to find the different effects on carbon intensity between government and enterprise R and D investment through a panel-regression model. Additionally, R and D investments on carbon intensity might crucially depend on the extent of development level. There is enormous distance in development in different areas in China. In areas with different levels of urbanization, due to industry choices and other factors, there are also differences in the environmental impact of government and enterprise R and D inputs. Therefore, we further explored the effect of changes at different urbanization stages by a threshold-regression model. The final question that remains to be answered is whether maximizing carbon-emission reduction requires constructing different R and D input subjects for regions with different levels of development. Understanding the distinction of the effect of different R and D sources on carbon emissions is of great significance to enact effective policies and conduct carbon-emission reductions from an R and D perspective. To solve the above questions, this paper takes the panel data of the R and D investment of the government and enterprises in 30 regions in China as a sample, and judges the differences in contribution between different R and D subjects. At the same time, a threshold-regression model was constructed to analyze the effect of different R and D subjects at different levels of development.

Thus, the distinction of this work from previous research lies in the following aspects. First, the effects of government and enterprise R and D investments on carbon intensity were compared in a model. Both effects were simultaneously taken into consideration, rather than focusing on one of them alone or just the total. Second, by using the panel-threshold model, and regarding urbanization level as the threshold variable, analysis of the impact of different R and D input entities on carbon intensity at different development levels was carried out. Therefore, based on the conclusions, the relative policy implications provide insight for the decision-making of the Chinese government on maximizing the effect of R and D investment on carbon intensity, as well as quickly reaching that goal. More details about the method and data are introduced in Section 2.

The structure of the rest of the paper is organized as follows: In Section 2, the research design, including model selection, variable screening, and researching hypothesis, are presented. The empirical results of the linear and nonlinear regressions are displayed in Section 3. The last section reaches conclusions on the research and gives relevant policy implications for the Chinese government.

2. Materials and Methods

First, we constructed a regression model based on provincial panel data and compared the effects of R and D investment from the government and enterprises on carbon intensity. Furthermore, considering the wide development distance between different regions in China, we assumed that, in areas with different development levels, the effects are also different. Therefore, we constructed the threshold-regression model regarding urbanization as a threshold variable and assuming a threshold of r. It was assumed that, once the urbanization level exceeded or fell below the r value, there would be significant differences in the effect of government and enterprise R and D investment on carbon intensity.

2.1. Panel-Regression Model

The panel-regression model was selected as a fundamental model. A panel-regression model is applicable to observations with multiple individuals over multiple periods, and has been widely utilized in empirical studies [25]. The Hausman test is first used to determine whether the fixed-effect model (FE) or the random-effect model (RE) is a more appropriate estimator [26]. To correct for heteroscedasticity and sequence correlation, a generalized least-squares (GLS) method could be a possible alternative method. In a review of the specific situation and previous research, some control variables were employed in our model, in which FDI, INDUS, and POP denote the federal direct investment, ratio of secondary industry to the total, and the population, respectively. The specific hypothesis model is as follows:

$$lnCI_{i,t} = \alpha_0 + \alpha_1 lnGOVI_{i,t} + \alpha_2 lnENTI_{i,t} + \alpha_3 lnFDI_{i,t} + \alpha_4 INDUS_{i,t} + \alpha_5 lnPOP_{i,t} + e_t \quad (1)$$

where subscript i (i = 1, 2, 3, ... , K, N) indicates regions, and subscript t (t = 1, 2, 3, ... , K, T) denotes time. α_m (m = 0, 1, ... , 7) are the coefficients to be calculated; CI is carbon intensity; GOVI and ENTI are the core independent variables, government R and D investment and enterprise R and D investment. Although much research has examined the factors influencing carbon emissions, the difference in our model lies in focusing on comparing the effect of government and enterprise R and D investment. In addition, it is necessary to consider that the effect may take some time after expenditure occurs. For this reason, a temporal lapse of 1–2 years of R and D investment was introduced for the analysis.

2.2. Threshold-Regression Model

The threshold was originally employed by Hansen [27,28], which allows nonlinear relationships between each independent variable and dependent variable at different intervals. Wu et al. argued that areas at different economic development stages present different carbon emissions characteristics [29]. Wu et al. advised that policy strategies for mitigating carbon emissions should be customized for different stages of urbanization [10]. Since there is a large gap in the development levels between different provinces in China, it is necessary to take the development level of different regions into consideration. Although previous studies have claimed that R and D is beneficial for carbon-emission reduction, further study with consideration of the different development stages is imperative so that carbon-reduction policies can be more targeted. To empirically analyze the effect, this work introduced the urbanization level of a region as a proxy of its development level.

Therefore, this paper assumes that there is a threshold r. The effects on carbon intensity show significant differences at different development levels. The double threshold-regression hypothesis model is as follows:

$$\begin{aligned} lnCI_{i,t} = \alpha_0 \quad & +\alpha_1 lnGOVI_{i,t} \times I(URB_{i,t} < r_1) + \alpha_2 lnGOVI_{i,t} \times I(r_1 \le URB_{i,t} \le r_2) \\ & +\alpha_3 lnGOVI_{i,t} \times I(URB_{i,t} > r_2) + \alpha_4 lnENTI_{i,t} \times I(URB_{i,t} < r_1) \\ & +\alpha_5 lnENTI_{i,t} \times I(r_1 \le URB_{i,t} \le r_2) + \alpha_6 lnENTI_{i,t} \times I(URB_{i,t} > r_2) \\ & +\alpha_7 lnFDI_{i,t} + \alpha_8 INDUS_{i,t} + \alpha_9 lnPOP_{i,t} + \varepsilon_t \end{aligned} \quad (2)$$

where α_m (m = 0, 1, ... , 7) are the coefficients to be calculated, and r_i (i = 1, 2,) represents the threshold value. $URB_{i,t}$ is the threshold of variable urbanization, which is based on the development level of the area. The multiple-threshold model can be extended accordingly.

2.3. Variables and Data

2.3.1. Explained Variable

Carbon intensity is defined as the ratio of CO_2 emissions to GDP. It takes a region's actual level of economic development into account, and can thus reflect a region's efforts to reduce carbon emissions [30]. In reflecting the actual result without inflation, GDP was calculated based on a constant year of 2009. So far, there are no direct carbon-emission observation data by province. However, CO_2 emissions are primarily generated from the burning of fossil fuels [5]. Considering this, existing research usually uses energy consumption to indirectly estimate carbon emissions. Drawing on relevant international data and the carbon-emission accounting method of the Intergovernmental Panel on Climate Change (IPCC) [31], the consumption of fossil energy in each province was selected as the basic data to calculate carbon emissions. Since Tibet's historical data are missing, the panel data for 30 provinces in China were collected as the research object. Referring to the China Energy Statistical Yearbook statistical standard, energy consumption can be divided into nine types: coal, gasoline, diesel, natural gas, kerosene, fuel oil, crude oil, electric power, and coke. Given that electric power is produced from other energy, it can be ignored in this work. The calculation formula is as follows:

$$CE = \sum_{i=1}^{8} (CO_2)_i = \sum_{i=1}^{8} E_i \times NCV_i \times CEF_i \tag{3}$$

In this formula, CE is the total amount of CO_2 emissions from all fossil-energy sources. NCV_i represents the average low calorific value of i energy, whose unit is KJ/kg·m^3. CEF_i represents the CO_2 emissions factor of i energy provided by the IPCC, whose unit is kg·CO_2/TJ. The NCV and CEF values of eight kinds of energy are displayed in Table 1.

Table 1. NCV and CEF values of eight kinds of energy.

	Coal	Gasoline	Diesel	Natural Gas	Kerosene	Fuel Oil	Crude Oil	Coke
NCV	20,908	43,070	42,652	38,931	43,070	41,816	41,816	28,435
CEF	95,533	70,000	74,100	56,100	71,500	77,400	73,300	107,000

2.3.2. Core Explanatory Variables

Technology innovation, which is mainly achieved through domestic R and D investment, plays a key role in balancing development and environment. R and D investment is also regarded as a measure of technology innovation in similar papers. This is also the reason why we chose R and D as the core explanatory variable. The data of R and D expenditures were collected from the China Science and Technology Statistics Yearbook. The two indicators are government and enterprise R and D expenditures.

2.3.3. Threshold Variable

As mentioned above, we assumed that the effects of R and D on carbon emissions may be influenced by the development level of the area. Considering relative studies, this paper chooses urbanization, the ratio of urban population to the total, to denote the level of development of each region [32,33].

2.3.4. Control Variables

To avoid other factors influencing result accuracy, this article takes other control variables into consideration, including FDI, population scale, and industry structure. FDI is helpful to improve the technology level. The existing literature has reported on the relationship between FDI and carbon emissions, finding that the overall effect of FDI is good for the environment [18,34], as it is considered to be conducive to a more efficient carbon reduction. Therefore, we introduce FDI as a control variable in this paper. There are two kinds of indicators of FDI in existing research. Acharkyya used a flow indicator focused on the impact of FDI fluctuations on carbon emissions, while Grimes, Kentor, and Jorgenson used a stock indicator focused on the effect of FDI scale [35,36]. A flow indicator was selected in this paper, which is the annual actual use of foreign capital in each province. Population scale is estimated by the number of people at the end of each year, which is directly from the China Statistics Yearbook. As for industry structure, secondary industry is the main factor that influences carbon intensity. Learning from Perkins and Neumayer's method, industry structure is estimated by the proportion of the secondary in GDP [37]. Similarly, data come from the China Statistics Yearbook.

2.4. Data Sources

The data in this paper are provincial panel data from the China Science and Technology Statistical Yearbook and the China Statistical Yearbook. Considering factors of data availability and statistical caliber changes, we selected 30 provinces as the research objective, and sample time interval was limited to 2009–2016. This time interval also reflects the key period for China to establish a national innovation system with enterprises as the mainstay. To exclude the influence of price factors and heteroscedasticity, all the data related to the value pattern were subjected to the 2009 index-based price index deflator and logarithmic transformation. The descriptive statistics of the main variables are presented in Table 2. The average investment of enterprise R and D investment is much higher than that of government R and D.

Table 2. Description of variables.

Variable	Definition	Unit	Mean	Std. Dev.	Min	Max
CI	CO_2 emissions divided by GDP	Ton/10^4 Yuan RMB	3.2416	2.0662	0.5562	10.28856
GOVI	Government R and D investment	10^8 Yuan RMB	70.9664	107.8413	2.7933	649.8845
ENTI	Enterprise R and D investment	10^8 Yuan RMB	253.0658	310.0617	4.8884	1454.074
POP	Population at the end of each year	10^4	4520.939	2702.857	568	10999
FDI	Actual use of foreign capita	10^8 Yuan RMB	455.3318	414.3027	0.8040679	1901.171
INDUS	Proportion of the secondary to the GDP	%	0.4617	.08303	0.1926	0.5905
URB	Proportion of urban population to the total	%	0.5628	0.1269	0.3641	0.8960

2.5. Multicollinearity Test

Considering several explanatory variables in the econometric model, the multicollinearity test was carried out to assess whether there is multicollinearity between the explanatory variables. If the variance inflation factor (VIF) were between 0 and 10, multicollinearity was acceptable. Results show that the VIF value of all variables are less than 10, which means multicollinearity in this model is acceptable.

3. Results

3.1. Linear Panel Regression Analysis

First, we identified the effects of government and enterprise R and D on carbon intensity using a fundamental panel-regression model. Based on Hausman's test, whose null hypothesis means that a random effect is more suitable, P value is greater than 0.05, without rejecting the null hypothesis. Thus, RE is regarded as a more appropriate estimator. A GLS estimator is employed in order to avoid heteroscedasticity and serial correlation. The results of the fundamental linear regression are presented in Table 3.

Table 3. Panel-regression results.

Variables	Original	Lag-1	Lag-2
lnGOVI	−0.05914 (0.239)		
lnENTI	−0.21862 (0.000)		
$lnGOVI_1$		−0.19221 (0.000)	
$lnENTI_1$		−0.04336 (0.250)	
$lnGOVI_2$			−0.18298 (0.000)
$lnENTI_2$			−0.04266 (0.172)
Constant	20.13513 (0.000)	20.2273 (0.000)	20.40902 (0.000)
lnFDI	−0.0583623 (0.025)	−0.0572226 (0.023)	−0.0635421 (0.015)
lnPOP	0.111707 (0.288)	0.0017492 (0.985)	−0.0302818 (0.750)
INDUS	1.583567 (0.000)	1.633302 (0.000)	1.699714 (0.000)
Wald chi2	95.11	87.63	91.94
Prob > chi2	0.0000	0.0000	0.0000

The original coefficients of government and enterprise R and D investment are −0.05914 and −0.21862. Enterprise input is more effective and significant in this model. In the one-year lag model, government and enterprise R and D investment effect is −0.19221 and −0.04336. In the two-year lag model, the two coefficients are −0.18298 and −0.04226. Government input tends to be more effective and significant. Concluding from Table 3, government and enterprise R and D both curb carbon intensity, while enterprise takes less time than government. From a long-term perspective, government investment is more effective. A possible reason for this phenomenon is that the foci of the two types of investment are different, as the government concentrates on fundamental research, which takes a long time to complete, and enterprises pay more attention to specific research and the utilization of technologies that emphasize a short payback time.

3.2. Threshold-Regression Model

Before using the threshold-regression model, the asymptotic distribution and accompanying probability of F-statistics in the form of three threshold models are calculated by the bootstrap self-sampling method for finding the most proper threshold-regression model. As shown in Table 4, the double-threshold model is significant. Therefore, double-threshold regression was employed for analysis. The robust results of the double threshold regression are shown in Table 5.

Table 4. Threshold-regression-model estimation results.

Threshold Model	*F*-Value	*P*-Value	1%	5%	10%
Single threshold	4.8596	0.0750	10.7560	5.7565	4.2124
Double threshold	6.1522	0.0290	10.2658	4.1972	2.3816
Triple threshold	5.9762	0.0720	13.8880	6.9905	4.9525

Table 5. Double-threshold-regression model results (Robust).

Variable	Coefficient	t-Statistic	*P*-Value
lnFDI	−0.0105	−0.3899	0.6972
lnPOP	−0.4720	−0.4650	0.6426
INDUS	0.3445	0.8798	0.3804
lnGOVI-1 (URB < 0.5334)	−0.0233	−0.2236	0.8234
lnENTI-1 (URB < 0.5334)	−0.3099	−4.1198	0.0001
lnGOVI-2 (0.5334 ≤ URB ≤ 0.5592)	−0.0828	−0.8011	0.4244
lnENTI-2 (0.5334 ≤ URB ≤ 0.5592)	−0.2457	−3.2507	0.0014
lnGOVI-3 (URB > 0.5592)	−0.1538	−1.8189	0.0710
lnENTI-3 (URB > 0.5592)	−0.1911	−2.8675	0.0048
F	6.1522		
P	0.0290		

The two thresholds of urbanization level are 0.5334 and 0.5592, which divide the sample into three intervals. The proportion of each interval is 48%, 11%, and 41%. In provinces with urbanization level below the first threshold, the effect of enterprise R and D investment on curbing carbon intensity is much more efficient and significant than that of the government. The coefficient of enterprise R and D investment at this interval is −0.3099 with a *p*-value of 0.0001. When it comes to the medium urbanization level, while enterprise investment is still more effective, with a coefficient of −0.2457 and a *p*-value of 0.0014, the distance of two coefficient becomes shorter. In regard to areas with higher urbanization, the two effects have a tendency to be consistent. The results indicate a different effect between different sources of R and D, which prompts us to find the underlying reasons behind it.

The urbanization level and the proportion of enterprise R and D investment of the 30 regions are presented in Figure 1. In most regions, enterprise R and D is much higher than that of government, with an enterprise R and D proportion value of more than 0.50. As mentioned above, the 30 provinces are divided in three intervals according to threshold values, urbanization level. The first stage is from Gansu to Shanxi, as shown in Figure 1. The second stage is from Ningxia to Hubei. The rest is the third stage. Concluding from the threshold-regression results, it was calculated that, in lower development areas, the effects of enterprise R and D on carbon emissions reduction is much larger. In provinces with high urbanization, governments tend to be more effective than at the lower urbanization level. However, no matter the stage, the effect of enterprise R and D is larger than that of government R and D, although there is a tendency to be consistent in higher urbanization level. From the proportion of R and D investment, we can see that the investment amount of enterprise R and D is much larger than that of government. Considering the scale, enterprise R and D takes up more carbon emissions than government R and D, which means that the government exchanges a small amount of R and D investment for a larger carbon-emission-reduction effect. This may be related to government investment strategies. Generally, government R and D investment follows international development trends, which pay much attention to fundamental R and D activities.

Based on the theory of comparative advantage, government input decisions are largely based on local resource endowments. Drawing on mature development routes and the industrial structure of developed regions, the government compares local resource-endowment advantages, selects key and high-tech industries that meet their comparative advantages, and prioritizes R and D investment to accelerate the upgrading and optimization of the local industrial structure. Therefore, government research and development can produce positive environmental effects.

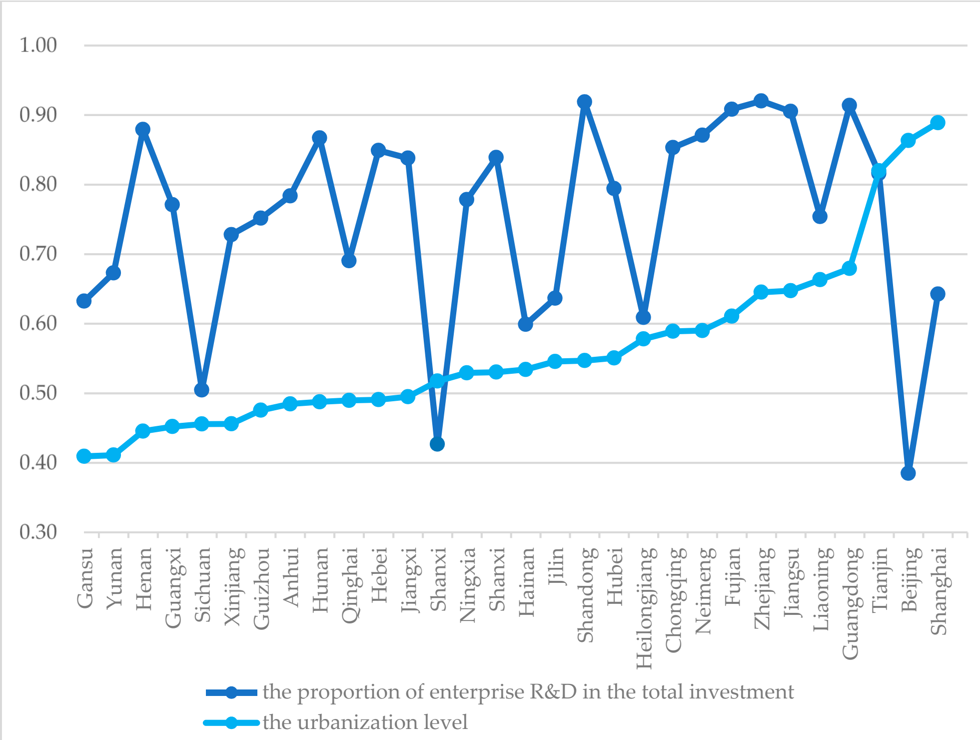

Figure 1. Urbanization level and enterprise R and D investment ratio of 30 regions (average of six years).

For deep analysis, samples can be divided into three intervals based on the two-threshold value: low, medium, and high development levels. Tables 6 and 7 show the ratio of government and enterprise R and D investment in the three intervals between 2011 and 2016. Generally, distribution is not balanced, with both focusing much more on high development-level areas. According to the above result, enterprise R and D is more effective at the low development level, which means that enterprise R and D investment is insufficient in low-developing areas where carbon-emission-reduction potential is high. Additionally, enterprises need to pay more attention to medium-developing areas. In regard to the government, the condition is different. Government R and D is more effective in high-developing areas. From the perspective of dynamic development, the ratio of R and D in high-developing areas tends to decrease, which needs improvement.

Table 6. Enterprise investment ratio.

Urbanization Stage	2011	2012	2013	2014	2015	2016
1	0.24	0.20	0.10	0.15	0.19	0.20
2	0.13	0.23	0.45	0.30	0.08	0.20
3	0.63	0.57	0.45	0.55	0.72	0.59

Table 7. Government investment ratio.

Urbanization Stage	2011	2012	2013	2014	2015	2016
1	0.24	0.19	0.17	0.23	0.19	0.13
2	0.16	0.27	0.29	0.18	0.22	0.54
3	0.60	0.54	0.54	0.59	0.59	0.32

4. Conclusions and Implications

Global warming, which is primarily caused by CO_2 emissions, has attracted attention from all around the world. As one of the world's largest emitters of carbon emissions, China is under great pressure to implement carbon-emission reduction. Based on this, a goal of carbon intensity peaking in 2030 was put forward by the Chinese government. Technology innovation plays a rather significant role in balancing economic growth and environmental conservation. Researchers have empirically testified that aggregate R and D is positively correlated with carbon-intensity reduction. Specifically, do enterprise and government R and D investments both curb carbon intensity? The Chinese government has proposed to establish a national innovation system that focuses on enterprise innovation. However, a comparison between the effects of government and enterprise R and D investment on carbon intensity has not been empirically examined. Thus, the question of which kind of innovation-system effect on carbon intensity is the most proper remains to be answered. Realizing this deficiency in the existing literature, this work aimed to explore the differences in the effect on carbon intensity between government and enterprise investment in R and D. Using the panel data of 30 provinces in China, this work examined the difference between different R and D sources on carbon intensity by panel regression. At the same time, the development level of different regions in China is spatially uneven, which leads to a difference in industrial structures. This may result in a dissimilar impact of different R and D subjects on carbon-emission reductions in different regions. Taking the development level of each region into account, we then used a threshold-regression model analyzing the different effects at different urbanization stages. The findings can be considered as an addition to the empirical literature on technological progress and carbon-emission mitigation.

4.1. Conclusions

Concluding from the calculated results, both government and enterprise R and D investment contribute to carbon-intensity reduction, although the primary goal of R and D investment is not the environment. From an environmental perspective, government R and D investment tends to come into effect in the long term, while enterprise R and D investment is more instant. This may mainly be because the foci of each investment are different. Moreover, the threshold-regression results show that the effects differ in different developing areas. In medium- and low-developing areas, enterprise R and D investment is more effective than government investment, while in high-developing areas, although enterprise R and D input still exceeds that of the government, there is a tendency of the effect to be consistent. When the input scale is taken into consideration, government R and D provides similar environmental benefits at a relatively lower cost. This may be due to differences in investment content. Comparing investment proportion in different areas, both government and enterprise R and D investment focus more on high-developing areas, which accounts for nearly 60% of the total. It is concluded that, though its effect is the most prominent, enterprise R and D investments in low-developing areas are not sufficient. From a dynamic perspective, increases in enterprise and government R and D investment are slow in areas with a high-potential environmental effect.

4.2. Policy Implications

Under the ambitious goal of mitigating carbon emissions, Chinese policy makers are facing an unprecedented challenge. Based on the above conclusions, we proposed some corresponding policy suggestions in R and D investment. The government may have to try to re-evaluate its R and D investment strategies to maximize the effect of both government and enterprise R and D investment on carbon-emission reduction. Some possible implications are as follows.

The government could lead in constructing enterprise-leading innovation in medium- and low-developing areas and draw on experience from developed areas. The government needs to fully mobilize the enthusiasm of enterprise innovation, further adjusting the relationship between the government and the market, as well as intensifying efforts to implement enterprise technological-innovation policy. It should construct an environment that encourages enterprises to carry out R and D innovation, and promote enterprises to implement fundamental and applied research. It should also strengthen the main position of enterprise innovation in R and D investment and improve the construction of enterprise R and D institutions. In view of the development characteristics of different regions, R and D investment and subjects should be established considering specific conditions. In undeveloped areas, enterprises can be regarded as the main body to improve innovation. In higher-developed areas, considering the government's high efficiency in input–output and the high effect of enterprises when creating development plans for areas, specific situations need to be analyzed.

On the basis of this study, it might prove fruitful to further investigate conditions in counterpart countries. Researchers have shown that the effect of R and D on technology is different from country to country. In this case, future-study directions are proposed to be comparing different countries' R and D investment effects on the environment considering multiple R and D subjects. The question that remains to be further explored is whether the result is the same with all countries, or if it is not the same under different backgrounds. Several future-study directions are thus proposed. Longer time and a wider research scope could also be taken into consideration for deep research.

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