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# Multiple Mediation Effects of Foreign Direct Investment on China's Carbon Productivity

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The paper investigates the internal mechanism of foreign direct investment (FDI) affecting carbon productivity through mediators. Based on data of China from 2000 to 2016, the mediation effect analysis method is used to build a single-step multiple mediator model. The empirical results show that FDI has a significant effect on the improvement of China's carbon productivity, which is mainly achieved by three mediators, namely, the industrial structure, the low carbon technology, and the energy structure. Then, the paper puts forward countermeasures that how to use FDI to improve China's carbon productivity, so that "Beautiful China" can be achieved.

Keywords: foreign direct investment, carbon productivity, mediation effect analysis, multiple mediation model

#### Introduction

During the 13th Five-Year Plan period, China's economic development has entered a new normal state. "Green" and "Open", the development concepts of the 13th Five-Year Plan, require China to "raise the level of open economy in a greater scope, wider area and deeper level", and "promote reform and development by opening up", as well as call for the realization of "Beautiful China" and "Green Development for the Country". On the 19th National Congress of the Communist Party of China (CPC) in October 2017, "Green Development", "Low-carbon Economy", and "Beautiful China" were mentioned many times. It is imperative to achieve relative reduction and to develop a low-carbon economy. The improvement of carbon productivity is the core requirement for the development of low-carbon economy (He & Su, 2009). In this new stage, how to make better use of high-level and high-quality foreign investment to increase carbon productivity so as to "optimize the growth of the environment" is an issue that must be considered in order to achieve green development.

Among the studies on the relationship between FDI and carbon emissions, the most studied is the impact of FDI on carbon emissions. With the concept of low carbon economy and sustainable development put forward, more and more scholars have shifted their attention from "absolute emission reduction" to "relative emission reduction". The study of FDI and carbon productivity is one of the most important aspects.

Perkins and Neumayer (2009) conducted an empirical research on the environmental efficiency spillover effects of FDI in 98 developing countries from 1980 to 2005, and found that FDI from economies with more efficient pollution control did not have an impact on domestic carbon productivity in developing countries. Liu

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and Hu (2016) used the spatial Durbin model, selected the data from 30 provinces in China from 2000 to 2012, and examined the impact of FDI on the carbon productivity in China and its sub-regions. It is found that FDI has a positive effect on the improvement of China's carbon productivity. The impact of FDI on regional carbon productivity is consistent with the "pollution halo" hypothesis, while the impact on carbon productivity in adjacent areas is consistent with the "pollution heaven" hypothesis. Based on the data of China's province from 1995-2012, Ma and Lu (2017) established the spatial panel data model, and found that FDI has a significantly positive spatial spillover effect on CO<sub>2</sub> emission efficiency. In addition to considering the regional differences, the industry differences have also drawn the scholars' attention. Guo, Zhang, and Lin (2014) used the panel data of China's industrial sectors from 2000 to 2011, and analyzed the impact of FDI on carbon productivity in China's industry as a whole and in different factor-intensive industries. It is concluded that FDI plays an important role in promoting carbon productivity in China's industry sector, labor-intensive industries and capital-intensive industries, while it has a negative impact on carbon productivity of resource-intensive industries.

Due to the differences in econometric method, data selection, index measurement, and research perspective, the conclusions of FDI's impact on carbon productivity are different. Most literatures agree that FDI has a positive effect on the increase of carbon productivity on the overall level. Few literatures pay much attention to the underlying mechanisms by which FDI affects carbon productivity through other variables. Therefore, on the basis of the theoretical mechanism of FDI affecting carbon productivity, this paper empirically analyzes the mechanism of FDI on China's carbon productivity from 2000 to 2016 by using the mediation effect analysis method.

### The Internal Mechanism of FDI Affecting Carbon Productivity

Carbon productivity is an important measure of the efficiency of single-factor carbon emissions (Ma, 2015). The carbon productivity can be measured by dividing GDP by CO<sub>2</sub> emissions. In essence, carbon productivity measures the output corresponding to the consumption of carbon resources per unit. It considers carbon as "an input that is implicit in energy and material products" (Pan, Zhuang, Zheng, Zhu, & Xie, 2010, p. 90), revealing the restrictive conditions for economic development. Thus, the concept of carbon productivity, a better reflection of the requirements for the development of low carbon economy, not only emphasizes the long-term sustainable economic growth, but also emphasizes the control of carbon emissions.

The Kaya identity and the STIRPAT model are two major ways to analyze the impact of CO<sub>2</sub> emissions. The Kaya identity states that the overall level of CO<sub>2</sub> emissions can be expressed as an equation consisting of four factors: population, GDP per capita, energy intensity of economy, and carbon content of energy. Its specific expression is as shown in equation (1) (Jiang, 2011):

$$C = \sum_{i} C_{i} = \sum_{i} G \times \frac{V_{i}}{G} \times \frac{E_{i}}{V_{i}} \times \frac{C_{i}}{E_{i}}$$

$$= \sum_{i} G \times S_{i} \times I_{i} \times F_{i}$$
(1)

where, C is a country's total carbon emissions.  $C_i$  is carbon emissions of sector i.  $V_i$  is the output of sector i, which is expressed by the added value of sector i.  $E_i$  is the energy consumption of sector i. G is the economic output expressed in GDP.  $S_i$  is the share of the output of sector i, namely  $V_i/G$ .  $I_i$  is the intensity of energy consumption in sector i, that is, the energy consumption per unit output  $(E_i/V_i)$ .  $F_i$  is the carbon content of

energy in sector i, which is the carbon emissions per unit energy consumption C<sub>i</sub>/E<sub>i</sub>.

The two sides of the equation (1) are converted to the reciprocal, and then multiplied by GDP:

$$\frac{\text{GDP}}{\text{CO}_{2}} = \frac{\text{GDP}}{\sum_{i} G \times S_{i} \times I_{i} \times F_{i}}$$

$$= \frac{1}{\sum_{i} S_{i} \times I_{i} \times F_{i}}$$
(2)

where,  $S_i$  (reflecting the industrial structure),  $I_i$  and  $F_i$  are the same as in equation (1). Equation (2) can also be expressed as the following equation:

As can be seen from the above formula, industry structure, energy efficiency, and energy structure are negatively correlated with the carbon productivity. With the Chinese economy entering a new normal state, its economic structure adjustment has shifted from the "231" type<sup>1</sup> to the "321" type. When the industrial structure is measured by the added value of the secondary industry in the GDP, the decline in this value means the improvement of the industrial structure in China. The industrial structure variable is on the denominator, so its decline is beneficial to the increase of carbon productivity. When energy efficiency is improved, such as the use of efficient low-carbon technologies, each unit of economic output will consume less energy and thus increase carbon productivity. When the energy structure is optimized, that is, reducing the consumption of fossil fuels with high CO<sub>2</sub> emissions, and increasing the use of non-carbon and clean energy, the energy consumption per unit will discharge less CO<sub>2</sub>, thereby increasing carbon productivity.

Another way to analyze the influencing factors of CO<sub>2</sub> emissions is the STIRPAT model. The estimated equation of STIRPAT model is shown in equation (4):

$$I = cP^{\beta_1}A^{\beta_2}T^{\beta_3}e \tag{4}$$

where, I is the impact of human beings on the environment, measuring by  $CO_2$  emissions. P (population) is measured by the size of a country's population. A (wealth) is measured by GDP per capita. T stands for the technology needed to reduce the negative impact on the environment. c is the coefficient.  $\beta_1$ ,  $\beta_2$ ,  $\beta_3$  are the index of P, A and T respectively. e is the error term.

Take the logarithm respectively on the two sides of the equation (4) to obtain the equation (5):

$$ln I = ln c + \beta_1 ln P + \beta_2 ln A + \beta_3 ln T + ln e 
= c' + \beta_1 ln P + \beta_2 ln A + \beta_3 ln T + e'$$
(5)

where, P can be decomposed into urban population/total population, i.e. urbanization level. T can be measured by energy intensity.

From the above analysis, the main factors that affect carbon productivity are industrial structure, energy efficiency, and energy structure. The transformation and upgrading of industrial structure, the improvement of energy efficiency, and the optimization of energy structure will increase carbon productivity. It is known from the STIRPAT model that a country's level of affluence (i.e. economic development level) and urbanization may also affect carbon productivity, since the formula for carbon productivity consists of both CO<sub>2</sub> emissions and

<sup>&</sup>lt;sup>1</sup> It means the proportion of the secondary industry in the national economy is much higher than the primary and tertiary industries.

GDP. Both of these two factors have a positive effect on CO<sub>2</sub> emissions and GDP growth, so their ultimate impact on carbon productivity depends on the difference in the effect on CO<sub>2</sub> emissions and GDP.

The theoretical analysis can be expressed in Figure 1 below:

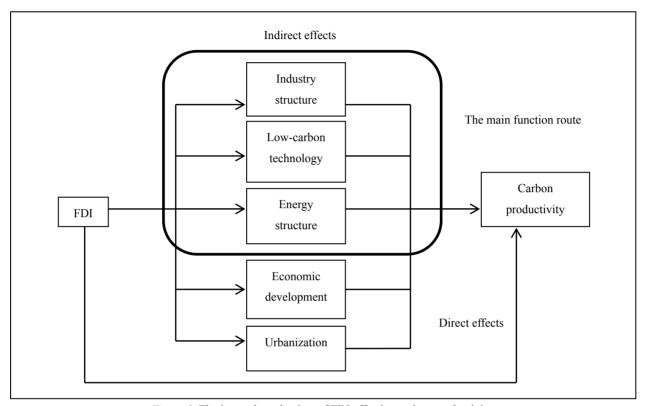


Figure 1. The internal mechanism of FDI affecting carbon productivity.

## **Empirical Analysis**

# **Mediation Effect Analysis**

If the influence of the independent variable (X) on the dependent variable (Y) is achieved by one or more variables, then the one or more variables are referred to as mediator variables (M) (Wen & Ye, 2014). The mediation effect involving multiple mediator variables is called multiple mediation effect. The model thus built is a multiple mediator model. For the sake of research needs and the simplicity of analysis, a single-step multiple mediator model is selected to analyze the internal mechanism of FDI affecting carbon productivity. The model is shown below:

$$\ln Y = \alpha + c \ln X + e \tag{6}$$

$$\ln M_i = \beta_i + a_i \ln X + e_i (i = 1, 2, 3, 4, 5)$$
(7)

$$\ln Y = \gamma + c' \ln X + \sum_{i=1}^{5} b_i \ln M_i + e'$$
 (8)

where,  $\alpha$ ,  $\beta_i$ , and  $\gamma$  are intercepts. e,  $e_i$ , and e' are residual errors. The independent variable X is FDI, the dependent variable Y is carbon productivity, the mediator variable  $M_1$  is industrial structure,  $M_2$  is low-carbon technology (i.e. energy efficiency),  $M_3$  is energy structure,  $M_4$  is economic development, and  $M_5$  is urbanization. c is the total effect of X on Y.  $a_i$  is the effect of X on  $M_i$ .  $b_i$  is the effect of  $M_i$  on Y, after

controlling the influence of X.  $a_ib_i$  is the specific indirect effect of X on Y via  $M_i$ . c' is the direct effect of X on Y, after controlling the influence of mediators. The total mediation effect is  $\sum_{i=1}^{5} a_ib_i$  or c-c'. All the variables are logarithmic in order to eliminate the influence of heteroscedasticity.

# Variable Explanation and Test of Time Series<sup>2</sup>

This paper takes 2000-2016 years as the sample interval, and all the data are from the national macro annual database of China Economic Information Network Statistics Database. The measurement and the explanation of variables are shown in Table 1.

Table 1

The Measurement of Variables and the Mechanism Affecting Carbon Productivity

Variable	Measurement	The mechanism affecting carbon productivity
Carbon productivity (cp)	The share of CO <sub>2</sub> emissions in real GDP (calculated at constant 2000 prices). Ten thousand yuan/ton of carbon dioxide.	/
FDI (fdi)	The actual use of foreign investment in the amount of foreign direct investment. 100 million yuan.	Two channels: direct impact on carbon productivity or indirect impact on carbon productivity through mediators.
Industry structure (is)	The added value of the secondary industry as a share of GDP. %.	(1) If the secondary industry accounted for a large proportion and FDI mainly flows to the high carbon industry→Carbon productivity declines. (2) If the proportion of FDI in the service sector rises→The optimization of industrial structure→Carbon productivity increases.
Low-carbon technology <sup>3</sup> (ei)	Total energy consumption as a share of real GDP. tce/10 thousand yuan.	The technology spillover effect of FDI $\rightarrow$ The improvement of low carbon technology in the host country $\rightarrow$ Increase in carbon productivity.
Energy structure (es)	The proportion of coal in the total energy consumption. %.	(1) The early stage of economic development: the high carbon industry has a high FDI, plus the stimulating effect of FDI on economic growth—The proportion of coal in total energy consumption increases—Reduction in carbon productivity. (2) Economic development reaches a certain level: FDI in high-tech and high value-added industries increases—The proportion of coal in total energy consumption decreases—Increase in carbon productivity.
Economic development (pgdp)	Real GDP divided by year-end population. 10 thousand yuan per person.	FDI promotes economic growth $\rightarrow$ (1) CO <sub>2</sub> emissions increase before economic growth exceeds a certain level $\rightarrow$ Increase or decrease in carbon productivity (uncertain, depending on the comparison of GDP growth rate to CO <sub>2</sub> emissions growth rate). (2) Economic growth exceeds a certain level, reducing CO <sub>2</sub> emissions $\rightarrow$ Increase in carbon productivity.
Urbanization (ur)	The proportion of urban population in total population. %.	FDI promotes the process of urbanization→It is beneficial to economic development and has both positive and negative effects on CO <sub>2</sub> emissions→Carbon productivity increases or decreases (uncertain).

The calculation of the national CO<sub>2</sub> emissions in Table 1 is based on the following formula:

<sup>&</sup>lt;sup>2</sup> Time series test and the subsequent empirical analysis are all used Stata12.0 software.

<sup>&</sup>lt;sup>3</sup> Low carbon technology is used to replace the broad technical level, which is more in line with the purpose of this study. The advantage of using energy efficiency (or energy intensity) as a measurement of low-carbon technology is that it reflects both the development of low-carbon technologies and the development of economy, reflecting the connotation of a low-carbon economy. If it is measured by environmental technical indicators, the scope is broader, and the relationship with carbon emissions is not very close.

$$C = \frac{44}{12} \sum_{i=1}^{3} \theta_i E \rho_i \tag{9}$$

where, C indicates the amount of  $CO_2(10,000 \text{ tons})$  emitted by fossil fuel combustion<sup>4</sup>.  $\theta_i$  is the share of fossil fuel i in the total energy consumption (%). E is the total energy consumption (10,000 tons of standard coal).  $\rho_i$  is the carbon (C) emission coefficient of energy i (tonne of carbon per tonne of standard coal), i.e. the carbon emission coefficient of  $CO_2$  generated from the complete combustion of one ton of standard coal. i=1, 2, 3 represents coal, oil, and natural gas respectively. 44/12 is a coefficient of carbon (C) emissions converted into  $CO_2$  emissions based on the relative atomic weights of carbon atoms and  $CO_2$  molecules.

In order to prevent the regression problem of fallacy, we choose DFGLS test and KPSS test to test the stability of the variables. Because the non-differential variables are non-stationary, the first-order difference of each variable is tested for stationarity.

Table 2
Results of Unit Root Test

Variable	DFGLS	KPSS	Conclusion	
D1 1	DFGLS(1) = -3.376	KPSS(0) = 0.097; KPSS(1) = 0.0674; KPSS(2) = 0.0654	G. 11	
D1.lncp	5% critical value: -3.164	5% critical value: 0.146	Stable	
D1.lnfdi	DFGLS(1) = -3.508	KPSS(0) = 0.0438; $KPSS(1) = 0.061$ ; $KPSS(2) = 0.0958$	Stable	
D1.Iniq1	5% critical value: -3.164	5% critical value: 0.146		
D1 Inia	DFGLS(1) = -1.566	KPSS(0) = 0.122; KPSS(1) = 0.118; KPSS(2) = 0.12	Stable	
D1.lnis	5% critical value: -3.164	5% critical value: 0.146		
D1 losi	DFGLS(1) = -4.627	KPSS(0) = 0.113; $KPSS(1) = 0.0729$ ; $KPSS(2) = 0.0698$	Stable	
D1.lnei	5% critical value: -3.164	5% critical value: 0.146		
DFGLS(1) = $-2.631$		KPSS(0) = 0.0518; $KPSS(1) = 0.102$ ; $KPSS(2) = 0.0882$	Stable	
D1.lnes	10% critical value: -2.390	5% critical value: 0.146	Stable	
D1.lnur	DFGLS(1) = -3.565	KPSS(0) = 0.0531; KPSS(1) = 0.0561; KPSS(2) = 0.0813	Stable	
	5% critical value: -3.164	5% critical value: 0.146		
D1 lnnada	DFGLS(2) = -0.478	= $-0.478$ KPSS(0) = $0.28$ ; KPSS(1) = $0.181$ ; KPSS(2) = $0.151$		
D1.lnpgdp	5% critical value: -2.848	5% critical value: 0.146	Unstable	
D2 langda	DFGLS(1) = $-4.540$	KPSS(0) = 0.0605; $KPSS(1) = 0.0695$ ; $KPSS(2) = 0.111$	0.11	
D2.lnpgdp	5% critical value: -2.883	5% critical value: 0.146	Stable	

*Notes.* 1. DFGLS (p) and KPSS (p) correspond to the statistics of the DFGLS test and the KPSS test, respectively, where p represents the lag order. 2. D1.varname represents the first difference of the variable, and D2.varname represents the second difference of the variable. 3. When the results of the DFGLS test and the KPSS test are contradictory, the results of the KPSS test are regarded as accurate, because the KPSS test can overcome the higher probability of making a Type II error (Chen, 2010, p. 274).

From Table 2, lncp, lnfdi, lnis, lnei, lnes, lnur are first-order single integer sequences I(1). lnpgdp is the second-order single integer sequence I(2), so it will be omitted in the following analysis. Because lncp and lnfdi are single integer sequences of the same order, cointegration analysis can be carried out.

Johansen test on lncp and lnfdi is conducted to determine whether there is a long-term, stable, and

 $<sup>^4</sup>$  Fossil fuels are the main source of  $CO_2$  emissions in China, and China's major fossil fuel consumption is coal, oil, and natural gas. Therefore, when calculating the national  $CO_2$  emissions, this paper uses coal, oil, and natural gas as the benchmark for the calculation of fossil fuels.

balanced relationship between these two variables. From the results of Table 3, we can see that there is a cointegration relationship between lncp and lnfdi at 5% significance level, that is, there is a long-term and stable equilibrium relationship between carbon productivity and FDI.

Table 3
Results of Johansen Cointegration Test

Test form $(c, t, p)$	Trace statistic	5% critical	Null value hypothesis H <sub>0</sub>	Alternative hypothesis H <sub>1</sub>	Conclusion
(1, 0, 4)	29.8793	15.41	h = 0	h > 0	Cointegration relationship exists
(1, 1, 4)	36.4504	18.17	h = 0	h > 0	Cointegration relationship exists
(0, 0, 4)	24.0540	12.53	h = 0	h > 0	Cointegration relationship exists

*Notes.* 1. h represents cointegration rank. 2. In the test form (c, t, p), "c = 0" means no constant, "c = 1" means a constant term; "t = 0" means no trend and "t = 1" means having a trend; p represents the lagged rank.

It is also necessary to examine whether FDI is the cause of changes in carbon productivity. As can be seen from Table 4, when the lag period is two, the null hypothesis is rejected at the significant level of 5%. In other words, FDI is the cause of changes in carbon productivity, and there are lagging effects of FDI on carbon productivity.

Table 4

Results of Granger Causality Test

Lag order	F statistics	P values	Conclusion
1	2.87	0.1140	Infdi does not Granger-cause Incp
2	4.42	0.0422	Infdi Granger-causes Incp
3	2.65	0.1304	Infdi does not Granger-cause Incp
4	2.82	0.1696	Infdi does not Granger-cause Incp
5	0.68	0.7212	Infdi does not Granger-cause Incp

Note. The null hypothesis (H<sub>0</sub>) is "Infdi does not Granger-cause Incp".

The correlations between explanatory variables and mediator variables are tested and the results are shown in Table 5. It is known from Table 5 that the correlation coefficients between multiple variables are significant. Therefore, the mediator variable lnur is abandoned by the stepwise regression method.

Table 5

Correlation Test Results

	lnfdi	lnis	lnei	lnes	lnur
lnfdi	1.0000				
lnis	-0.4337	1.0000			
lnei	-0.7569*	0.8434*	1.0000		
lnes	-0.4355	0.9682*	0.8709*	1.0000	
lnur	0.9819*	-0.5071*	-0.8075*	-0.5042*	1.0000

*Note*. The star (\*) means the correlation coefficients significant at the 5% level or better.

## Estimation and Test of the Single-Step Multiple Mediator Model

Because multiple equations are involved in the estimation, the error terms between the different equations may be correlated with each other. The seemingly uncorrelated regression is performed on the equation (7) and

(8), and the ordinary least squares regression is performed on the equation (6). The regression results are shown in Table 6.

Table 6
Estimation Results for the Single-Step Multiple Mediator Model

Dependent variable	Equation (6)	Equation (7.1)	Equation (7.2)	Equation (7.3)	Equation (8)
Independent variable	lncp	lnis	lnei	lnes	lncp
lnfdi	0.461***	-0.078**	-0.391***	-0.072**	0.029***
IIIIQI	(4.41)	(-1.98)	(-4.78)	(-1.99)	(5.66)
lnis					-0.114**
IIIIS	-	-	-	-	(-2.12)
1					-1.023***
lnei	-	-	-	-	(-55.67)
1					-0.310***
lnes	-	-	-	-	(-4.24)
R-squared	0.5641	0.1881	0.5729	0.1896	0.9997
Adj. R-squared	0.5350	-	-	-	-
F-statistic or Chi <sup>2</sup> -statistic	19.41***	3.94**	22.80***	3.98**	64037.18***

*Notes.* 1. Equation (7.1), (7.2), and (7.3) correspond to the equation (7) containing mediator variable  $M_1$  (industrial structure),  $M_2$  (low carbon technology) and  $M_3$  (energy structure). 2. The parenthesis in the equation (6) is t value, and the parentheses in the other equations are Z values. 3. \*\*\*, \*\*, \* indicate significant at 1%, 5%, 10% levels respectively. 4. Because the intercept item has no substantial meaning in the analysis of mediating effect, it is omitted here.

In equation (6), the total effect of FDI on carbon productivity is c = 0.461, which is significant at the 1% level. This shows that FDI has a significant positive impact on carbon productivity, and the increase of FDI by 1% will result in the increase of carbon productivity by 0.461%.

In equation (7.1),  $a_1 = -0.078$  and is significant at the 5% level, indicating that FDI can significantly improve the industrial structure. For every 1% increase in FDI,  $M_1$  will decrease by 0.078%. In equation (8),  $b_1 = -0.114$ , and is significant at the 5% level, indicating that an improvement in industrial structure has a significant effect on the increase of carbon productivity. For every 1% decrease in  $M_1$ , the carbon productivity will increase by 0.114%. This is consistent with the previous conclusion that the industrial structure and carbon productivity are negatively correlated. Since  $a_1$  and  $b_1$  are both significant, the mediation effect of the industrial structure is significant, which is  $a_1b_1 = 0.009$ .

In equation (7.2),  $a_2 = -0.391$  and is significant at the 1% level. For every 1% increase in FDI,  $M_2$  will decrease by 0.391%. This shows that the inflow of FDI has a significant role in promoting the improvement of low carbon technology in China. In equation (8),  $b_2 = -1.023$ , which is significant at the 1% level, indicating that the promotion of low carbon technology has a significant contribution to the improvement of carbon productivity. For every 1% reduction in  $M_2$ , carbon productivity will increase by 1.023%. This is consistent with the conclusion of the relationship between energy efficiency and carbon productivity in formula (3). Because  $a_2$  and  $b_2$  are both significant at the 1% level, the mediating effect of low carbon technology is significant, and its value is  $a_2b_2 = 0.400$ .

In equation (7.3),  $a_3 = -0.072$  and is significant at the 5% level, indicating that the increase in FDI has a significant effect on the decline in the share of coal in total energy consumption. For every 1% increase in FDI,  $M_3$  will decrease by 0.072%. In equation (8),  $b_3 = -0.310$  and is significant at the 1% level, indicating that improvements in energy consumption structure can significantly increase the carbon productivity. For every 1%

reduction in  $M_3$ , carbon productivity will increase by 0.310%. This verifies the negative correlation between energy consumption structure and carbon productivity. Since  $a_3$  and  $b_3$  are significant, the energy structure mediation effect is significant with a value of  $a_3b_3 = 0.022$ .

Because the sequential test results of coefficients ( $a_i$ ,  $b_i$ , I=1,2,3) are significant, the individual mediating effects of industrial structure, low carbon technology, and energy structure are significant. In equation (8), the direct effect of FDI on carbon productivity, c'=0.029, is significant at the 1% level, indicating that in addition to the three mediator variables, there may be other mediators that play a role in the intrinsic mechanisms by which FDI affects carbon productivity.

Then the Bootstrap test is used to examine the total mediation effect and the difference of the individual mediation effects. In this paper, the non-parametric percentile Bootstrap method and the bias-corrected non-parametric percentile Bootstrap method are used to test the single-step multiple mediator model<sup>5</sup>. If the confidence interval does not include 0, the mediation effect is statistically significant.

Table 7

Results of the Bootstrap Test

Mediation effect	Observed coefficient	95% percentile confidence interval	95% bias-corrected confidence interval	Conclusion
$a_1b_1 + a_2b_2 + a_3b_3$	0.431	(0.224, 0.791)	(0.223, 0.789)	Significant
$a_2b_2 - a_3b_3$	0.378	(0.219, 0.651)	(0.230, 0.680)	Significant
$a_2b_2 - a_1b_1$	0.391	(0.225, 0.688)	(0.220, 0.682)	Significant
$a_3b_3 - a_1b_1$	0.013	(-0.006, 0.091)	(-0.007, 0.083)	Not significant
$a_2b_2 - (a_1b_1 + a_3b_3)$	0.369	(0.224, 0.616)	(0.234, 0.634)	Significant

As can be seen from Table 7, the total mediation effect is 0.431, and it is significant, which shows that it is reasonable to regard the industrial structure, low carbon technology, and energy structure as the mediator variables at the same time. The values of  $a_2b_2 - a_3b_3$  and  $a_2b_2 - a_1b_1$  are all significant, indicating that there are significant differences between the impact path through low-carbon technology and the impact path through energy structure and industrial structure respectively. The value of  $a_2b_2 - (a_1b_1 + a_3b_3)$  is 0.369, and it is significant, indicating that the mediating effect of low-carbon technology is 0.369 higher than that of industry structure and energy structure. However,  $a_3b_3 - a_1b_1$  is not significant, indicating that there is no significant difference between the impact path through the energy structure and the impact path through the industrial structure.

Under the premise of a significant total mediation effect, the proportion of specific mediation effect in the total mediation effect can be calculated. Among the total mediator effects, the mediating effect of the low-carbon technology is the largest, accounting for 92.8%. The proportion of total mediating effect in the total effect is 0.935. This shows that among the effect of FDI on carbon productivity, 93.5% can be explained by the mediating effect.

From the above analysis, the path chart of FDI affecting carbon productivity can be drawn, as shown in Figure 2. Figure 2 shows a single-step multiple mediator model with three mediator variables. Number "1" in the figure corresponds to the equation (6), which describes the total effect of FDI on carbon productivity.

<sup>&</sup>lt;sup>5</sup> Because the bias-corrected non-parametric percentile Bootstrap method obtains a bias-corrected confidence interval, it is more robust than the nonparametric percentile Bootstrap method. However, under some conditions, the first type error rate of the bias-corrected non-parametric percentile Bootstrap method will be higher than the set significance level.

Number "2" in the figure corresponds to equations (7.1), (7.2), and (7.3), describing the direct effect of FDI on carbon productivity and the indirect effects via three mediators.

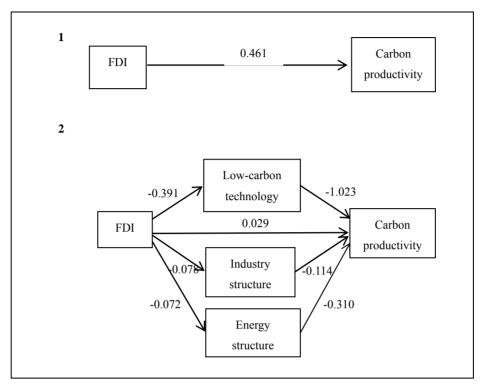


Figure 2. The path chart of FDI affecting carbon productivity.

## **Conclusions and Suggestions**

From the above analysis, we can see that the impact of FDI on carbon productivity is mainly achieved through three mediator variables: industrial structure, low carbon technology, and energy structure. FDI can promote carbon productivity by optimizing the industrial structure, improving the energy consumption structure, spreading the low-carbon technologies and management practices. The direct impact of FDI on raising carbon productivity is small, but positive. Through the mediation effects and the direct effect of FDI, the increase of FDI has a significant promoting effect on carbon productivity.

In the internal mechanism of FDI affecting carbon productivity, the mediation effect of low carbon technology is the highest. This shows that FDI has a significant technology spillover effect between 2000 and 2016. With the improvement of China's economic development level and the adjustment of its economic structure, China's ability to absorb and utilize the advanced foreign technological knowledge has been increasing. The mediation effect of industrial structure and energy structure are equivalent. Between 2000 and 2016, the proportion of FDI in service industry gradually exceeded that in manufacturing industry, which was conducive to the increase of carbon productivity. Although the proportion of coal in total energy consumption in China has declined every year since 2011, the proportion of coal consumption in China is 62% in 2016, which is still high. As a result, the mediating effect of energy structure is smaller than that of low-carbon technology.

Based on the above conclusions, it is necessary to gradually and orderly broaden the field of FDI, introducing more FDI in low carbon industry and high technology industry, and create a good business

environment for attracting foreign enterprises that have a positive effect on the development of low-carbon economy in China. For the opening of service industry, we should integrate domestic standards, norms, and systems with those of other countries. In improving the quality of foreign investment, the local government's investment policy is the key, especially in the county-level cities and towns. In order to rapidly increase the level of economic growth in the short term, these less-developed areas are extremely prone to "race to the bottom". Therefore, it is necessary for the central government to differentiate incentive policies and measures for the provinces, autonomous regions, and municipalities, and then they formulate targeted policies for their respective regions to prevent local governments from introducing foreign capital with extremely low environmental standards. In terms of business environment, we should further promote the unification of domestic and foreign enterprises' policies, reform the domestic administrative approval process, reduce or cancel government fees and increase the measures of facilitating enterprises.

Increasing the introduction of low-carbon environmental protection technology, and strengthening the exchange of emission reduction technologies and practices between enterprises are other measures. Developed countries, such as Britain and Germany, are among the best in the world in clean growth, low-carbon technologies, and policy innovations. By introducing these countries' foreign capital in the fields like renewable energy, industrial biotechnology, and high-end equipment manufacturing, making full use of the low-carbon technology spillover effect of FDI, the development of low-carbon economy in China can reach a higher level.

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