

EFFECT OF LOW CARBON ECONOMY ON ENTERPRISE COMPETITIVENESS: A MULTIPLE MEDIATION MODEL

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Abstract. The low-carbon economy is an economic model based on low energy consumption, low pollution and low emissions. According to some research, a low-carbon economy model can have a significant impact on a company's competitiveness. However, there are two different types of views on the relationship between environmental regulation and corporate competitiveness. This study uses a method of testing multiple mediations that can explain many complex internal mechanisms in the field of organizational behavior science. The results show that the low carbon economy has a positive effect on technology innovation, and this effect will influence enterprise competitiveness through sustainable development. We also found that the compound multiple mediation model has an advantage in explaining the problems involved with low carbon economy and enterprise competitiveness.

Keywords: *low energy consumption, sustainable development, CO₂ emissions, technology innovation, enterprise strategic*

Introduction

Low-carbon development is a strategic decision that human beings have to face and seek opportunities under the dual pressure of financial crisis and climate and environmental crisis (Louche et al., 2019; Gong, et al., 2018). It will bring about a series of fundamental changes in the whole economy, society and enterprises. It is not an exaggeration to call it a technological revolution or an industrial revolution. The arrival of the low-carbon era will lead to profound changes in the standards of our enterprises, including value standards and evaluation systems (Niamir et al., 2018). Opportunities of emerging industrial revolution brewing under the development mode of low-carbon economy urgently need the strong support of enterprise strategic planning and thus promote the economic development mode from a high carbon economy to low carbon economy (Barron et al., 2018; Du, et al., 2018).

Low-carbon economy refers to an economic development pattern that achieves a win-win situation for economic and social development and ecological environmental protection (Shimada et al., 2007). Under the guidance of the concept of sustainable development, through technical innovation, system innovation, industrial transformation, new energy development and other means to reduce the high carbon energy consumption of coal, oil, greenhouse gas emissions and so on (Hu et al., 2011). With the increase of the global population and the continued economic growth, the environmental problems and consequences caused by the use of fossil energy and other conventional sources have received more and more attention. Environmental hazards such as exhaust gas pollution, photochemical smog, water pollution and acid rain, as well as global climate change caused by the rise of carbon dioxide concentration in the atmosphere, will cause serious consequences (Foxon, 2011). Therefore, a series of new concepts and policies have emerged, such as carbon footprint, low-carbon economy, low-carbon technology, low-carbon development, low-carbon lifestyle, low-carbon society, low-carbon city and a low-carbon world (Nader, 2009; Liu, 2018; Lefevre et al., 2018; Ervine, 2018).

The arrival of the low-carbon era will lead to profound changes in the standards of our enterprises, including value standards and evaluation systems. Under the guidance of low-carbon economic policies, enterprises must shift from the traditional growth model to directly applying the new century's innovative technology and innovation mechanism and achieving sustainable social development through low-carbon economic model and lifestyle (Tavoni et al., 2012; Li and Sun, 2018; Ropeik, 2017). Opportunities of emerging industrial revolution brewing under the development mode of low-carbon economy urgently need the strong support of enterprise strategic planning and thus promote the economic development mode from a high carbon economy to low carbon economy. From this perspective, the low-carbon economy is both a limitation and an opportunity. Therefore, this study mainly explores the effect of the low-carbon economy on enterprise competitiveness and uses a method of multiple mediation models to reveal the internal mechanism.

Research background and hypotheses

Low carbon economy

The low-carbon economy is an economic model based on low energy consumption, low pollution, and low emissions. The essence of the low-carbon economy is the problem of high energy utilization efficiency and clean energy structure. In the context of global warming, the low-carbon revolution with energy efficiency and low emissions as the core is gradually changing many industrial ecosystems. Therefore, companies must focus on developing low-carbon technologies to seize the opportunities and industry commanding heights.

Tavoni et al. (2012) believe that with the increase in income, the industrial and consumption structures have changed. At the same time, when people began to pay attention to the issue of protecting the environment, the phenomenon of environmental degradation gradually slowed down or even disappeared. Glaser (2003) concluded that CO₂ emissions are in an “N” rather than inverted “U” relationship with economic growth. Smale et al. (2006) believe that in the early stage of industrialization, with the development of the economy and the increase of per capita income, the per capita CO₂ emissions will be at a higher level.

Low-carbon economy and enterprise competitiveness

There are two different types of views on the relationship between environmental regulation and corporate competitiveness. The first perspective is that the implementation of environmental regulations will lead to a decline in the competitiveness of enterprises. The government implements environmental regulations and companies need to add special costs to eliminate pollution and reduce their environmental impact to meet environmental standards. The environmental standards require that the production costs of enterprises will rise sharply, which will directly affect their competitiveness. Healy and Barry (2017) argued that environmental regulation is not only not conducive to technological innovation, but because the entire process of environmental control will cause companies to be forced to transform the original production process, which will have an impact on technological innovation. Garay and Font (2012) pointed out that in order to adapt to environmental regulations, the company's processes are becoming more and more complex, resulting in a large management difficulty, and the management costs

are increasing, eventually resulting in a decline in corporate profits and a decline in competitiveness. Ortiz et al. (2009) showed that as environmental governance costs increase, it is increasingly difficult for individual companies to achieve a win-win situation for both environment and competitiveness. The stricter environmental regulations will inevitably worsen the business conditions of enterprises. At the same time, the benefits of adopting new technologies are not enough to boost the profits of enterprises. While environmental protection regulation improves the overall social welfare, it will lead to a decline in industrial production efficiency, and enterprises pay a higher price for it.

However, other scholars believe that companies will actively seek environmental technology innovation and develop environmental products in response to environmental policies, competitors and consumers (Rijsberman, 2017; Ervine, 2018). As a result, the sustainability of the industry will naturally increase, thus causing the competitiveness to transform and transition around the green. From a dynamic perspective, strict environmental standards will encourage companies to accelerate the pace of product innovation, and encourage enterprises to continuously improve the inefficiency in the production process, and reluctantly. The effective use of resources, through continuous technological innovation, brings about a reduction in pollution and an increase in output, resolving the contradiction between the environment and competitiveness, and achieving a win-win situation in which both economic performance and environmental performance are simultaneously changed. At the same time, this technological innovation will also enable companies that comply with environmental standards to gain a “first mover advantage”. Managers should take environmental improvement as an opportunity to add economic value and competitive advantage, and should not only be an annoying cost or threat. Based on this, this paper proposes:

H: Low carbon economy influence enterprise competitiveness through a multiple mediation model, see in Figure 1.

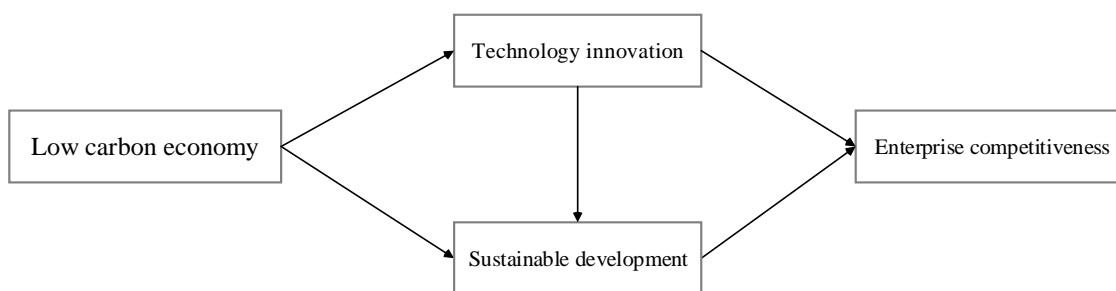


Figure 1. Theory research model

Methodology

Sample source

In this paper, we used the multiple mediation models to analyze the relationship between low carbon economy and enterprise competitiveness. First, we selected 42 enterprises in China and got their basic information before the investigation. Then, during the investigation, the managers answered a 20-question questionnaire including all the indicators of this study. The descriptive statistics are in *Table 1*.

Table 1. Descriptive statistics (n = 42)

Variable	Low carbon economy	Technology innovation	Sustainable development	Enterprise competitiveness
Low carbon economy	1			
Technology innovation	.639**	1		
Sustainable development	.674**	.751**	1	
Enterprise competitiveness	.641**	.691**	.706**	1

**Correlation is significant at the 0.01 level (double tail)

Multiple mediation model

Ordinary least squares mediation model

The ordinary least squares (OLS) mediation model always present in the form of three regression equations (Preacher and Hayes, 2008):

$$y_i = \beta_{01} + \tau x_i + \varepsilon_{1i} \quad (\text{Eq.1})$$

$$m_i = \beta_{02} + \alpha x_i + \varepsilon_{2i} \quad (\text{Eq.2})$$

$$y_i = \beta_{03} + \beta m_i + \tau' x_i + \varepsilon_{3i} \quad (\text{Eq.3})$$

In these equations (Eqs. 1–3), y_i is the dependent variable, m_i is the mediating variable, and x_i is the independent variable. The coefficient between the independent variable and the dependent variable is represented by τ , and τ' is the coefficient adjusted for the influence of the mediating variable. β_{01} , β_{02} , and β_{03} represent the intercept in the three equations.

To calculate the multiple mediation effects, there are three points to lay the foundation. First, β in the third equation is relating to the dependent variable and the mediating variable. Second, α in the second equation is relating to the independent variable and the mediating variable. Third, the product of α and β is the estimator of the indirect effect, and τ' is the estimator of the direct effect.

The variance of the indirect effect $\sigma_{\alpha\beta}^2$ is based on the variance of α and β , and it is derived using a second-order Taylor series in Equation 4:

$$\sigma_{\alpha\beta}^2 = \alpha^2 \sigma_{\beta}^2 + \beta^2 \sigma_{\alpha}^2 + \sigma_{\alpha}^2 \sigma_{\beta}^2 \quad (\text{Eq.4})$$

If α and β are nonzero values, according to Monte Carlo studies, for a sample size of 100 or more in a simulation model, all three variance estimators appear to have a relative bias of less than 5%. So Confidence limits are constructed in Equation 5:

$$\alpha\beta \pm z_{1-\omega/2} \times \sigma_{\alpha\beta} \quad (\text{Eq.5})$$

where $z_{1-\omega/2}$ is the value on the z-distribution corresponding to the desired Type I error rate, ω .

As the indirect effect is the product of α and β , and the estimates are normally distributed. The distribution of the product is an index to test the indirect effect. In other words, we can test the indirect effect based on $z_\alpha z_\beta$, where $z_\alpha = \alpha / \sigma_\alpha$ and $z_\beta = \alpha / \sigma_\beta$.

The central moments of the process are as follows (Eqs. 6–9).

$$\text{Mean : } M_1 = \mu = z_\alpha z_\beta \quad (\text{Eq.6})$$

$$\text{Variance : } M_2 = \sigma^2 = z_\alpha^2 + z_\beta^2 + 1 \quad (\text{Eq.7})$$

$$\text{Skewness : } M_3 = \alpha_3 = \frac{6(z_\alpha z_\beta)}{(z_\alpha^2 + z_\beta^2 + 1)^{3/2}} \quad (\text{Eq.8})$$

$$\text{Kurtosis : } M_4 = \alpha_4 = \frac{12(z_\alpha^2 + z_\beta^2) + 6}{(z_\alpha^2 + z_\beta^2 + 1)^2} \quad (\text{Eq.9})$$

To get the analytical solution, a Bessel function with a purely imaginary argument is used in *Equation 10*.

$$\begin{aligned} f(z_\alpha z_\beta) = & \frac{e^{-(z_\alpha^2 + z_\beta^2)/2}}{\pi} \left[\sum_0 K_0 + (z_\alpha^2 + z_\beta^2) \frac{z_\alpha z_\beta}{2!} \sum_2 K_1 \right. \\ & + (z_\alpha^4 + z_\beta^4) \frac{(z_\alpha z_\beta)^2}{4!} \sum_4 K_2 \\ & \left. + (z_\alpha^6 + z_\beta^6) \frac{|z_\alpha z_\beta|^3}{6!} \sum_6 K_3 + \dots \right] \end{aligned} \quad (\text{Eq.10})$$

In the equation, K is the Bessel function and Σ is a Laurent series in *Equation 11*.

$$\sum_r (z_\alpha, z_\beta, z_\alpha z_\beta) = 1 + \frac{z_\alpha z_\beta z_\alpha z_\beta}{r+1} + \frac{(z_\alpha z_\beta z_\alpha z_\beta)^2}{(r+1)^2 2!} + \frac{(z_\alpha z_\beta z_\alpha z_\beta)^3}{(r+1)^3 3!} + \dots \quad (\text{Eq.11})$$

In the equation, r is the order of the Laurent series in *Equation 12*.

$$(r+k)^k = (r+k)(r+k-1)\dots(r+1) \quad (\text{Eq.12})$$

To calculate the 95% standard normal confidence limits, it used a Standardized Critical Value (SCV). According to Meeker's suggestion (Meeker et al., 1982), it found the Critical Value (CV) in the table, and then convert to the standardized metric of the regression coefficient (α and β) in *Equation 13*.

$$SCV = \frac{CV - z_\alpha z_\beta}{\sqrt{z_\alpha^2 + z_\beta^2 + 1}} \quad (\text{Eq.13})$$

Parallel multiple mediation model

Parallel multiple mediation model reflects a situation in which multiple variables simultaneously mediate between the independent and dependent variable, see in *Figure 2*.

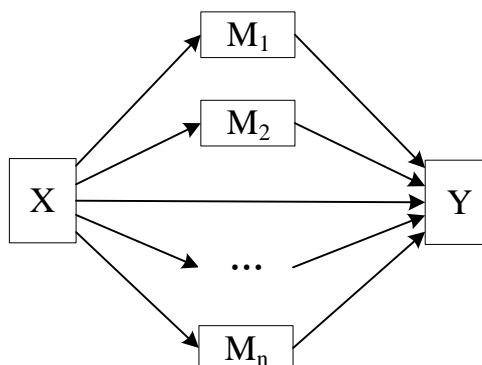


Figure 2. *Parallel multiple mediations model*

The relationship between the dependent variables, independent variables and multiple mediating variables are as follows (*Eqs. 14–16*).

$$Y = \tau X + \varepsilon_X \quad (\text{Eq.14})$$

$$M_i = \alpha_i X + \varepsilon_i \quad (\text{Eq.15})$$

$$Y = \sum_{i=1}^n \beta_i M_i + \tau' X + \varepsilon \quad (\text{Eq.16})$$

where $i = 1 \dots n$, τ' is the direct effect and τ is the total effect between the dependent variable and independent variable, $\alpha_i \beta_i$ is the indirect effect of each mediation path in *Equation 17*.

$$\tau = \tau' + \sum_{i=1}^n \alpha_i \beta_i \quad (\text{Eq.17})$$

The analysis of parallel multiple mediating effects generally includes three parts: first, the estimation and test of the overall mediating effect; second, the estimation and test of special mediating effects; third, the comparison between the mediating effects.

The total indirect effect is $\tau - \tau'$, or $\sum_{i=1}^n \alpha_i \beta_i$.

According to Mackinnon's suggestion (Mackinnon et al., 2007), the McGuigan and Langholtz effect size was to test the significance of the total indirect effect in Equation 18.

$$t_{N-2} = \frac{\tau - \tau'}{\sqrt{\sigma_{\tau}^2 + \sigma_{\tau'}^2 - 2\rho_{\tau\tau'}\sigma_{\tau}\sigma_{\tau'}}} \quad (\text{Eq.18})$$

In the equation, σ_{τ} is the standard error of τ , $\sigma_{\tau'}$ is the standard error of τ' , and $\rho_{\tau\tau'}$ is the regression coefficient between τ and τ' .

Compound multiple mediation model

The compound multiple mediations model is composed of the both parallel and serial mediating path see in Figure 3.

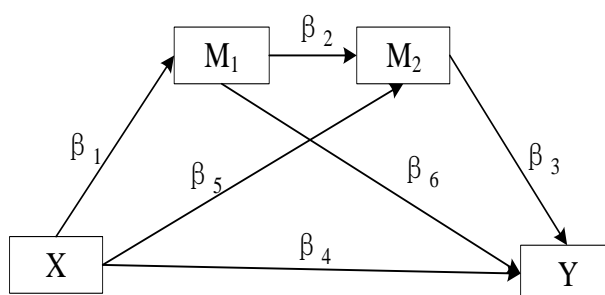


Figure 3 Compound multiple mediations model

To test the indirect effect, we need to estimate the following three equations (Eqs. 19–21).

$$M_1 = \beta_{01} + \beta_1 X + \varepsilon_1 \quad (\text{Eq.19})$$

$$M_2 = \beta_{02} + \beta_2 M_1 + \beta_5 X + \varepsilon_2 \quad (\text{Eq.20})$$

$$Y = \beta_{03} + \beta_4 X + \beta_3 M_2 + \beta_6 M_1 + \varepsilon_3 \quad (\text{Eq.21})$$

Results and analysis

Mediation test

To test the significance of the indirect effect, the multivariate delta method, the unbiased estimate method, and the exact variance estimate method are used. The following is a brief introduction to the principle of these three methods.

Multivariate delta method

As can be seen above, β_1 , β_2 and β_3 are the regression coefficients. The product of these three coefficients divides the mediation effect by the estimated standard error. The

derivation of the three estimators of the variance of β_1 , β_2 and β_3 are as follows in Equation 22.

$$\begin{aligned}
 s_{multi}^2 &= \left[\frac{\partial \beta_1 \beta_2 \beta_3}{\partial \beta_1}, \frac{\partial \beta_1 \beta_2 \beta_3}{\partial \beta_2}, \frac{\partial \beta_1 \beta_2 \beta_3}{\partial \beta_3} \right] \begin{bmatrix} s_{\beta_1}^2 & s_{\beta_1 \beta_2} & s_{\beta_1 \beta_3} \\ s_{\beta_2 \beta_1} & s_{\beta_2}^2 & s_{\beta_2 \beta_3} \\ s_{\beta_3 \beta_1} & s_{\beta_3 \beta_2} & s_{\beta_3}^2 \end{bmatrix} \begin{bmatrix} \frac{\partial \beta_1 \beta_2 \beta_3}{\partial \beta_1} \\ \frac{\partial \beta_1 \beta_2 \beta_3}{\partial \beta_2} \\ \frac{\partial \beta_1 \beta_2 \beta_3}{\partial \beta_3} \end{bmatrix} \\
 &= [\beta_2 \beta_3, \beta_1 \beta_3, \beta_1 \beta_2] \begin{bmatrix} s_{\beta_1}^2 & s_{\beta_1 \beta_2} & s_{\beta_1 \beta_3} \\ s_{\beta_2 \beta_1} & s_{\beta_2}^2 & s_{\beta_2 \beta_3} \\ s_{\beta_3 \beta_1} & s_{\beta_3 \beta_2} & s_{\beta_3}^2 \end{bmatrix} \begin{bmatrix} \beta_2 \beta_3 \\ \beta_1 \beta_3 \\ \beta_1 \beta_2 \end{bmatrix} \quad (\text{Eq.22}) \\
 &= \beta_2^2 \beta_3^2 s_{\beta_1}^2 + \beta_1^2 \beta_3^2 s_{\beta_2}^2 + \beta_1^2 \beta_2^2 s_{\beta_3}^2 + 2\beta_1 \beta_2 \beta_3^2 s_{\beta_1 \beta_2} \\
 &\quad + 2\beta_1 \beta_2^2 \beta_3 s_{\beta_1 \beta_3} + 2\beta_1^2 \beta_2 \beta_3 s_{\beta_2 \beta_3}
 \end{aligned}$$

In the compound multiple mediation model, β_1 , β_2 and β_3 are independent, so the last three items are zero, and the variance in the multivariate delta estimate method is in Equation 23.

$$s_{multi}^2 = \beta_2^2 \beta_3^2 s_{\beta_1}^2 + \beta_1^2 \beta_3^2 s_{\beta_2}^2 + \beta_1^2 \beta_2^2 s_{\beta_3}^2 \quad (\text{Eq.23})$$

Unbiased estimate method

The unbiased estimate method is based on the work of Goodman (1960). His research gives a suggestion for the calculation of unbiased estimate variance of two independent random variables. Extending his research to this case, the equation is in Equation 24.

$$\begin{aligned}
 s_{unbiased}^2 &= (\beta_1^2 - s_{\beta_1}^2)(\beta_2^2 - s_{\beta_2}^2)s_{\beta_3}^2 + (\beta_1^2 - s_{\beta_1}^2)(\beta_3^2 - s_{\beta_3}^2)s_{\beta_2}^2 \\
 &\quad + (\beta_2^2 - s_{\beta_2}^2)(\beta_3^2 - s_{\beta_3}^2)s_{\beta_1}^2 + (\beta_1^2 - s_{\beta_1}^2)s_{\beta_2}^2 s_{\beta_3}^2 \\
 &\quad + (\beta_2^2 - s_{\beta_2}^2)s_{\beta_1}^2 s_{\beta_3}^2 + (\beta_3^2 - s_{\beta_3}^2)s_{\beta_1}^2 s_{\beta_2}^2 + s_{\beta_1}^2 s_{\beta_2}^2 s_{\beta_3}^2 \\
 &= (\beta_1^2 \beta_2^2 s_{\beta_3}^2 - \beta_1^2 s_{\beta_2}^2 s_{\beta_3}^2 + s_{\beta_1}^2 s_{\beta_2}^2 s_{\beta_3}^2 - \beta_2^2 s_{\beta_1}^2 s_{\beta_3}^2) + (\beta_1^2 \beta_3^2 s_{\beta_2}^2 \\
 &\quad - \beta_1^2 s_{\beta_3}^2 s_{\beta_2}^2 - \beta_3^2 s_{\beta_1}^2 s_{\beta_2}^2 + s_{\beta_1}^2 s_{\beta_2}^2 s_{\beta_3}^2) + (\beta_2^2 \beta_3^2 s_{\beta_1}^2 - \beta_2^2 s_{\beta_3}^2 s_{\beta_1}^2 \\
 &\quad - \beta_3^2 s_{\beta_2}^2 s_{\beta_1}^2 + s_{\beta_1}^2 s_{\beta_2}^2 s_{\beta_3}^2) + (\beta_1^2 s_{\beta_2}^2 s_{\beta_3}^2 - s_{\beta_1}^2 s_{\beta_2}^2 s_{\beta_3}^2) + (\beta_2^2 s_{\beta_1}^2 s_{\beta_3}^2 \\
 &\quad - s_{\beta_2}^2 s_{\beta_1}^2 s_{\beta_3}^2) + (\beta_3^2 s_{\beta_1}^2 s_{\beta_2}^2 - s_{\beta_3}^2 s_{\beta_1}^2 s_{\beta_2}^2) + s_{\beta_1}^2 s_{\beta_2}^2 s_{\beta_3}^2 \\
 &= \beta_1^2 s_{\beta_2}^2 s_{\beta_3}^2 + \beta_1^2 \beta_3^2 s_{\beta_2}^2 + \beta_2^2 \beta_3^2 s_{\beta_1}^2 - \beta_1^2 s_{\beta_2}^2 s_{\beta_3}^2 - \beta_2^2 s_{\beta_3}^2 s_{\beta_1}^2 \\
 &\quad - \beta_3^2 s_{\beta_1}^2 s_{\beta_2}^2 + s_{\beta_1}^2 s_{\beta_2}^2 s_{\beta_3}^2
 \end{aligned} \quad (\text{Eq.24})$$

Exact variance estimate method

The exact variance estimate method is also an extension of Goodman’s research. In this method, it draws into the square of the coefficient of variation to accomplish the calculation. For variable β_i , the function is in *Equations 25 and 26*.

$$G(b_i) = s_{\beta_i}^2 / \beta_i^2 \tag{Eq.25}$$

$$\begin{aligned} s_{exact}^2 &= (\beta_1\beta_2\beta_3)^2 [G(\beta_1) + G(\beta_2) + 2G(\beta_3) + 2G(\beta_1)G(\beta_2)G(\beta_3) \\ &\quad + G(\beta_2)G(\beta_3)] \\ &= (\beta_1\beta_2\beta_3)^2 \left[\frac{s_{\beta_1}^2}{\beta_1^2} + \frac{s_{\beta_2}^2}{\beta_2^2} + \frac{2s_{\beta_3}^2}{\beta_3^2} + 2 \times \frac{s_{\beta_1}^2}{\beta_1^2} \times \frac{s_{\beta_2}^2}{\beta_2^2} \times \frac{s_{\beta_3}^2}{\beta_3^2} + \frac{s_{\beta_2}^2}{\beta_2^2} \times \frac{s_{\beta_3}^2}{\beta_3^2} \right] \tag{Eq.26} \\ &= \beta_2^2\beta_3^2s_{\beta_1}^2 + \beta_1^2\beta_3^2s_{\beta_2}^2 + \beta_1^2\beta_2^2s_{\beta_3}^2 + \beta_1^2s_{\beta_2}^2s_{\beta_3}^2 + \beta_2^2s_{\beta_3}^2s_{\beta_1}^2 \\ &\quad + \beta_3^2s_{\beta_1}^2s_{\beta_2}^2 + s_{\beta_1}^2s_{\beta_2}^2s_{\beta_3}^2 \end{aligned}$$

According to Sobel’s suggestion (Sobel, 1982), we calculate the confidence intervals for each method to test the significance of the model in *Equation 27*.

$$95\% \text{ confidence interval} = \beta_1\beta_2\beta_3 \pm z_{.975} (s_{type}^2)^{1/2} \tag{Eq.27}$$

In the equation above, $z_{.975} = 1.96$, and type is multivariate delta, unbiased or exact. The hypothesis can be confirmed when the 95% confidence interval does not include zero.

Table 2 shows the results for the methods. As the confidence interval of the model did not include zero, the hypothesis of this study was tested.

Table 2. Results for each method applied to data

Method	Estimate	Standard error	Test	Hypothesis test result
Joint significance	$\beta_1=0.862$	0.071	T=12.074, P<0.001	Support hypothesis
	$\beta_2=0.844$	0.055	T=15.428, P<0.001	
	$\beta_3=0.589$	0.079	T=7.414, P<0.001	
Multivariate delta method	$\beta_1\beta_2\beta_3=0.429$	0.08	95% CI=[0.272,0.586]	Support hypothesis
Unbiased estimate method	$\beta_1\beta_2\beta_3=0.429$	0.079	95% CI=[0.274,0.584]	Support hypothesis
Exact variance estimate method	$\beta_1\beta_2\beta_3=0.429$	0.084	95% CI=[0.264,0.594]	Support hypothesis
Percentile bootstrap	$\beta_1\beta_2\beta_3=0.429$	—	95% CI=[0.266,0.577]	Support hypothesis
Bias-corrected bootstrap	$\beta_1\beta_2\beta_3=0.429$	—	95% CI=[0.279,0.600]	Support hypothesis

Optimal model selection

By the comparison of the three multiple mediation models (see in *Table 3*), we found that the total indirect effect of the compound multiple mediation model was much better than the series multiple mediations model and parallel multiple mediation model. This

indicates that the compound multiple mediation model was more suitable for the practical problem in this study.

Table 3. Comparison of three multiple mediation models

Model	Indirect effect	Standard error	Lower 95%CI	Upper 95%CI
Series multiple mediations model	0.177	0.069	0.067	0.327
Parallel multiple mediation model	0.331	0.082	0.177	0.465
Compound multiple mediation model	0.509	0.057	0.407	0.606

Conclusion

In this paper, we proposed a multiple mediation model to explore the relationship between low carbon economy and enterprise competitiveness. The results show that the low-carbon economy has a positive effect on technology innovation, and this effect will influence enterprise competitiveness through sustainable development. We also found that the compound multiple mediation model has more advantage to explain the problems involved with low carbon economy and enterprise competitiveness. Our finding has made an effective supplement to the study of low carbon economy and enterprise competitiveness theory. Therefore, in the future research on enterprise competitiveness, scholars should pay more attention to technological change and sustainable development to adapt to the low-carbon economy. For example, it is very important to explore how to balance the relationship between technological innovation and sustainable development.

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