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ENERGY CARBON PERFORMANCE CURSE: AN ANALYSIS BASED ON THE ECONOMIC RESTRUCTURING STICKINESS

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Abstract. Although natural resource's negative impacts on economic growth have been extensively explored, its curse on energy carbon performance may remain ignored. Combining theoretical analysis, this paper further examines the curse of mineral resource dependence on energy carbon performance and the specific mechanism. In 2019, if optimal production is achieved in all sample cities, China would reduce electricity consumption by 42.941% and carbon emissions by 43.958%. Compared to non-resource-based cities, the potential ratios of energy savings and carbon reduction in resource-based cities are 5.403% and 6.059% higher, respectively. When the mineral resource dependence is less than 0.042%, it contributes to energy carbon performance, but when the mineral resource dependence exceeds 0.042%, higher mineral resource dependence implies more serious energy carbon performance curse, which explains the coexistence of resource blessing and resource curse. Economic restructuring stickiness caused by mineral resource dependence serves as a key mechanism for energy carbon performance curse, and energy, factor and industry restructuring stickiness are specific channels for this mechanism.

Keywords: mineral resource dependence, energy carbon performance, economic restructuring, transmission mechanism.

JEL Classification: C43, O13, Q32.

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1. Introduction

Industrialization and urbanization have contributed to prosperous economic growth, but have also led to energy depletion and climate warming, which raises worldwide concerns about the human living environment (Rehman et al., 2021). International environmental agreements, including *Kyoto Protocol*, *Paris Agreement* and *Global Environment Convention*, have already established a global governance framework to balance ecology and economy, contributing greatly to the sustainability of world's economy (Ciplet & Roberts, 2017; Aklin & Mildenberger, 2020). However, the *WMO Provisional State of the Global Climate 2022* stated that the global average temperature for the decade 2013–2022 is 1.14 °C higher than the pre-industrial period (1850–1900), which implies that climate warming still threatens the survival of humanity. And carbon emission reduction is regarded as the main way to mitigate climate warming (Mikhaylov et al., 2020; Yoro & Daramola, 2020). Therefore, economic transformation to low carbon becomes urgent for global sustainable development and human survival.

At the cost of environmental pollution and energy waste, China has achieved world-renowned economic development (Liang et al., 2022; Lyu et al., 2023). However, in terms of environmental performance, China still remains relatively backward compared to developed countries[1] (Figure 1). And according to the *World Bank*, energy intensity in China was 1.24 times that of US and 1.81 times that of Japan in 2015, which means that China's energy waste remains serious (Lyu et al., 2023). Nevertheless, China is now actively undertaking a significant responsibility for global carbon reduction (Wu et al., 2020). At the 75th session of UNGA, China proposed carbon reduction goals of carbon peak and carbon neutrality, which inevitably requires China to achieve low-carbon development as soon as possible, and means that identifying the hindering factors for low-carbon economy matters more. The resource curse remains a potential constraint (Fan et al., 2022; Nwani et al., 2021; Wu et al., 2021). Publicly available data from the *World Bank* shows that the ratios of natural resource rents to GDP in developing countries are much higher than those in developed countries (Figure 2), implying more serious natural resource dependence in developing countries such as China (Ascher & Healy, 1990; Mavrotas et al., 2011). Thus, the resource curse poses a challenge to the low-carbon transition in developing countries.

In traditional economic theory, abundant natural resources are treated as the cornerstone of industrialization and economic growth (Adams et al., 2019; Van der Ploeg, 2011). However, Auty (1993) proposed the resource curse hypothesis that abundant natural resources act as a constraint on the economic growth. Since then, numerous scholars have collected a wealth of empirical evidence on the resource curse (Basedau & Lay, 2009; Goldberg et al., 2008; He & Mou, 2020; Libman, 2013; Mehrara, 2009; Ross, 1999; Sachs & Warner, 1997; Williams, 2011), arguing that overdependence on natural resources does suppress regional economic growth (Adhvaryu et al., 2018; Axbard et al., 2021; Badeeb et al., 2017; Fan et al., 2022; Friedrichs & Inderwildi, 2013; Hodler, 2006; Van der Ploeg, 2011; Shao & Yang, 2014). In fact, overdependence on natural resources also leads to more serious energy waste and carbon emissions (Chiroleu-Assouline et al., 2020; Li et al., 2019; Lovins & Cohen, 2011), which is described as carbon curse (Abraham, 2021; Fan et al., 2022; Friedrichs & Inderwildi, 2013; Nwani et al., 2021; Wu et al., 2021). However, the carbon curse hypothesis tends to only discuss the relationship between natural resources and carbon emissions, failing to consider the role of natural resources in economic growth. Discussing the resource curse without ignoring the positive role of natural resources in economic growth is what this study has been emphasizing, but this may be disregarded by the carbon curse hypothesis (Abraham, 2021; Friedrichs & Inderwildi, 2013), which exaggerates the negative aspects of natural resources (Badeeb et al., 2017). Ignoring the dual effects of natural resources, which are positive for economic growth while being negative for carbon emissions, will inadvertently underestimate the comprehensive impact of the resource curse on human society.

To break the resource curse, its generation mechanism has been intensively investigated (Cheng et al., 2021). The price volatility of natural resources tends to lead to trade fluctuations in natural resource exporting countries, which is detrimental to stable economic growth and

[1] Environmental Performance Index, jointly published by Yale University and Columbia University.

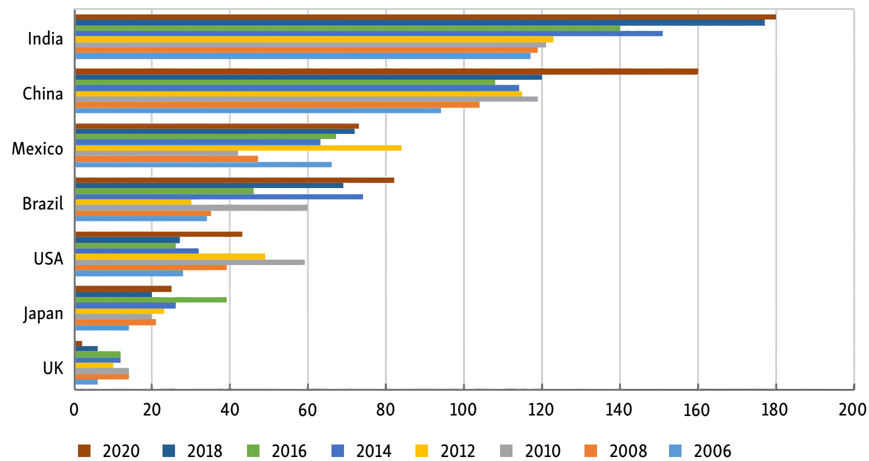

Figure 1. Environmental performance rankings

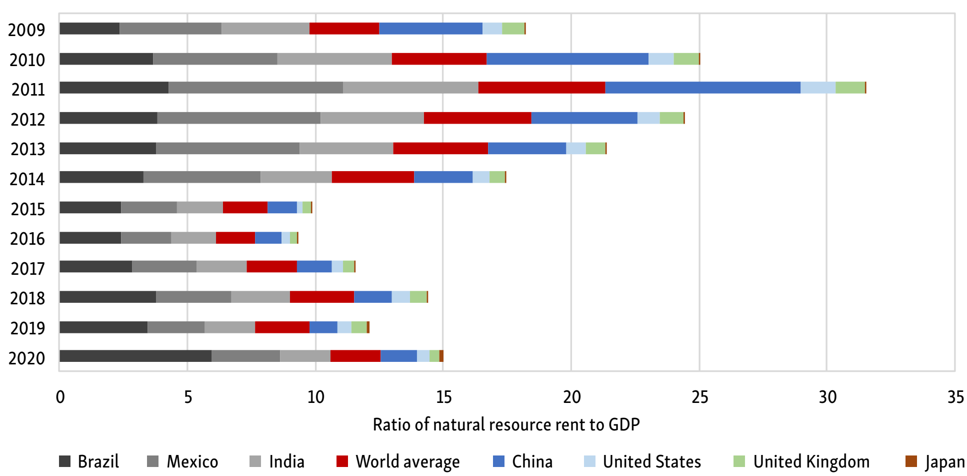

Figure 2. Ratio of natural resource rent to GDP during 2009–2020

thus results in resource curse (Asif et al., 2020; Frankel, 2010; Mikesell, 1997; Ross, 1999). And abundant natural resources tend to encourage rent-seeking behavior, which weakens the quality of the political system and is detrimental to long-term economic growth (Abed & Gupta, 2002; Hillman, 2004; Leite & Weidmann, 1999). In addition, the crowding-out effects of natural resources on economic drivers such as human capital and technological innovation are commonly acknowledged to blame for persistent economic decline (Douglas & Walker, 2017). However, most existing studies focus on superficial impact pathways such as external market shocks and institutional environment distortions. These studies have a relatively narrow analytical scope: they fail to delve into the internal structure of the economic system and overlook the long-term lock-in effect of resource dependence on the economic structure itself. Furthermore, most studies do not fully examine the economic structural stickiness caused by resource dependence through the solidification of high-carbon energy structures and single-industry structures. Abundant natural resources tend to make cities overly reliant on high-carbon energy (Altenburg, 2011; Dong et al., 2020). Nevertheless, a single-industry structure dominated by resource-based industries not only increases the difficulty of economic transition but also intensifies resistance to environmental improvement – specifically, it leads to a rise in the curvature of the Environmental Kuznets Curve (EKC) (Bithas & Kalimeris, 2015; Lin & Jiang, 2009). Economic structural stickiness manifests as transition rigidity in the industrial structure, energy system, and technological pathways of resource-dependent regions (Zhao et al., 2025). Analyzing the internal mechanism of how mineral resource dependence affects energy carbon performance from this perspective breaks through the exogenous shock paradigm of the traditional resource curse. It provides a new theoretical entry point for understanding the structural barriers to the low-carbon transition of resource-based economies and holds significant policy implications for breaking carbon lock-in and promoting structural emission reduction.

The marginal contributions and innovation of this paper are threefold. Firstly, this paper extends the traditional resource curse hypothesis to energy carbon performance curse hypothesis. The carbon curse hypothesis, which focuses only on carbon emissions, magnifies the curse and negates the positive role of natural resources in economic growth. Our energy carbon performance curse hypothesis not only takes into account the positive impact of natural resources on economic growth, but also identifies an important factor that impedes low-carbon economies in developing countries. Secondly, this paper revises the econometric models in existing studies and discusses the inverted U-shaped relationship between mineral resource dependence and ECP, demonstrating that the controversy between the resource curse and resource blessing may only result from differences in the samples distributed on different sides of the inverted U-shaped relationship. This, to a certain extent, explains the coexistence of the resource blessing and the resource curse, and also provides specific references for the formulation of energy conservation and emission reduction policies. Thirdly, from the perspective of economic restructuring stickiness, this paper explores the transmission mechanism through which natural resource dependence influences urban energy carbon performance, focusing on four dimensions: energy restructuring, factor restructuring, industrial restructuring, and human capital restructuring. By highlighting the dynamic linkages and adjustment resistances among internal structures of the economic system, it breaks through the static and unitary analytical limitations of existing literature. Additionally, we investigate the path dependence and lock-in effects induced by economic restructuring stickiness, revealing the deep-seated structural contradictions in the transition from resource-based to low-carbon economies. This provides important value for global resource-dependent economies to address the dilemmas of low-carbon transformation.

The rest of this paper is organized as follows: Section 2 explains the generation mechanism of energy carbon performance curse. Section 3 describes the model and data employed. Section 4 analyzes the empirical results. Section 5 proposes the discussion.

2. Mechanism analysis

2.1. Direct effect

Mineral resource development directly influences urban energy carbon performance in both positive and negative ways. The positive impacts stem from the resource dividends generated by mineral resource development. Firstly, based on the Heckscher-Ohlin (H-O) model and comparative advantage theory, resource-based cities typically prioritize specialized mining and processing as their core development path relying on abundant mineral endowments. The short-term competitive advantages formed by this specialization in factor costs and technological accumulation enhance urban energy carbon performance. Secondly, natural resource rents constitute an important component of national wealth creation and economic growth (Xu et al., 2024). When governments achieve budget balance and fiscal surpluses, they are more likely to allocate funds to support long-term R&D of low-carbon technologies and increase public spending on education and science (Chen et al., 2023; Lee et al., 2024). Such investments help form a virtuous cycle between economic growth and environmental benefits, thereby improving urban energy carbon performance. Additionally, mineral resources serve not only as the material foundation of traditional industrialization but also as key raw materials for clean energy technologies. Critical minerals such as copper, lithium, nickel, cobalt, and rare earth elements are essential for producing energy storage batteries, wind turbines, and solar panels (Wang et al., 2023). Thus, the development and utilization of mineral resources reduce raw material costs, promote the popularization of clean technologies, and enhance urban energy carbon performance.

The negative impacts derive from the structural rigidity caused by long-term mineral resource dependence. In terms of energy structure, the fossil fuel-dominated energy system suppresses enterprises' low-carbon innovation motivation (Abraham, 2021; Friedrich & Inderwildi, 2013). Enterprises in mineral-rich regions have significant cost advantages in energy procurement due to local cheap fossil energy, making the marginal cost of traditional energy use consistently lower than the marginal benefit of energy-saving technologies. As a result, these enterprises show significantly lower willingness to invest in improving energy efficiency. This cycle of "low-cost energy dependence-technological substitution inertia" eventually forms an "energy efficiency trap", leading enterprises to prefer expanding fossil energy inputs over technological innovation to maintain production capacity, thereby inhibiting the improvement of energy carbon performance. From the perspective of consumption structure, the long-term fossil energy-based consumption pattern has created a cognitive blind spot for low-carbon products among consumers (Unruh, 2000; Chen et al., 2025), hindering spontaneous green consumption upgrading. The terminal demand for minerals like coal and oil directly drives the production lock-in of high-energy consumption and high-carbon emission products (Holmberg, 2008). To meet existing consumption demands, enterprises continue to invest in traditional high-carbon technologies, further reinforcing the energy-intensive industrial structure and leading to a decline in urban energy carbon performance.

In summary, the impact of mineral resource development on urban energy carbon performance is twofold, and the final effect depends on the dynamic game between the short-term dividends and long-term structural rigidity of resource development. As a basic input factor, mineral resources can effectively reduce raw material costs, accelerate urban industrialization, and increase economic output per unit of energy input in the early stage of development. In this case, the positive "resource dividend" dominates. However, as the degree of mineral resource dependence increases, urban development gradually forms path dependence and structural rigidity, with production factors excessively concentrated in resource-intensive sectors, causing cities to fall into the "resource curse", which inhibits energy carbon performance (Lee & He, 2022). Therefore, when mineral resource dependence reaches a certain threshold, the negative "energy and consumption structure rigidity" takes the dominant role, exerting a negative impact on urban energy carbon performance. In conclusion, the impact of mineral resource development on urban energy carbon performance depends on the degree of dependence, manifesting as a non-linear inverted U-shaped relationship.

2.2. Indirect effect

The essence of economic restructuring lies in enhancing growth quality and transforming development models by optimizing the allocation and interaction among core components within the economic system. Energy structure, factor structure, industrial structure, and human capital structure constitute the critical components of economic system operations, collectively forming the core dimensions of economic restructuring (Guo & Zhao, 2025). Energy serves as the foundational input factor for economic activities, and adjustments to its structure directly impact production cost efficiency and environmental externalities. The type, allocation methods, and efficiency of factors directly determine the form, function, and upgrading potential of economic structure. Adjusting the factor structure is the core pathway to overcoming diminishing marginal returns and enhancing total factor productivity. Industrial restructuring reflects shifts in demand structure and the dynamic evolution of comparative advantage, representing an inevitable law of economic development revealed by the Kuznets curve and the Pareto-Clark theorem. Adjustments to human capital structure focus on upgrading labor quality and skill alignment. As the core driver of endogenous growth theory, it directly determines technological innovation capacity and the efficiency of industrial transformation. Therefore, we define economic restructuring as a composite concept encompassing four dimensions: energy structure, factor structure, industrial structure, and human capital structure (Wu et al., 2012).

In the short term, resource rents generated by mineral resource dependence provide the initial capital accumulation necessary to break through the poverty trap (Rostow, 1960). The influx of high-value resource revenues is efficiently allocated through channels such as public finance or private-sector reinvestment. This enables resource-dependent regions to significantly enhance their economic capabilities in the short run, facilitating capital accumulation and capacity building in energy security, education development, and industrial growth. This process lays the foundation for economic restructuring. However, in the long term, due to the comparative advantage trap, mineral resource-based regions tend to form a monolithic economic system dominated by resource industries (Bithas & Kalimeris, 2015; Oqubay, 2015), which in turn makes it more difficult to restructure the economy (Wang et al., 2019b), and this economic phenomenon is defined as economic restructuring stickiness in this paper. More fatally, this stickiness makes it more difficult to implement low-carbon policies due to the lack of technological linkages and economic support from other industries (Andersen & Wicken, 2021). Thus, economic restructuring stickiness induced by overdependence on mineral resources works as an important generation mechanism for energy carbon performance curse.

Firstly, on the one hand, in the short term, resource rents generated from mineral extraction can provide critical financial support for energy transition. During the early stages of economic development when capital is scarce, substantial investments are required to upgrade energy infrastructure, enhance energy efficiency, deploy clean energy generation, and develop low-carbon technologies. Resource rents serve as a vital source of funding to meet these urgent investment needs. On the other hand, a cleaner energy transition gets shackled by mineral resource dependence. Mineral resource endowments not only weaken the willingness to invest in R&D for energy-efficient technologies (Wang et al., 2021), but also form market barriers to renewable energy sources such as solar (Abraham, 2021; Zeng et al., 2025), which leads to highly carbon-intensive energy consumption habits and energy structure (Li et al., 2019).

Secondly, on the one hand, mineral resource exploitation provides a source of initial capital accumulation for economies suffering from capital scarcity. The short-term injection of resource rents can remarkably elevate the gross social investment rate, thereby breaking through the capital accumulation barrier posited by the Lewis Model. Meanwhile, the expansion of the resource sector absorbs surplus agricultural labor, increasing the proportion of non-agricultural employment. The mining industry and its related service sectors facilitate the accumulation of basic human capital by creating skilled jobs. On the other hand, massive labour and capital in resource-based regions are locked up in resource industries, which is detrimental to the development of high-value-added sectors such as the financial industry (Addison & Cornia, 2001; Menaldo, 2016). This, in turn, hinders the process of factor capitalization and low-carbon development (Tian, 2018).

Thirdly, on the one hand, in China, mineral resources are owned by local governments. The fiscal revenue generated from mineral resource development constitutes a significant source of funding for public education. By increasing investment in basic and higher education, the government can improve educational infrastructure and enhance educational quality, thereby boosting the overall quality of the labor force. On the other hand, as most scholars have concluded, the weak demand for highly educated and skilled labor in the resource industries has resulted in the fact that education for advanced human capital (Bridge, 2008; Dinkelman, 2011; Lockett & Thompson, 2001), which matters for technological innovation and carbon reduction (Poortinga et al., 2004; Esquivias et al., 2022; Wen et al., 2022), has been neglected.

Finally, in the short run, the capital accumulation generated by mineral resource development can be channeled into investments in industrial infrastructure, the procurement of advanced production equipment, and the expansion of production scale. This facilitates the transformation of the economy from a traditional agricultural-dominated structure to a modern one with increased shares of industry and services. The substantial capital injection enables rapid expansion of the industrial sector, attracting surplus agricultural labor to shift towards industry and services, thereby accelerating the process of industrial structure adjustment. However, in the long run, the comparative advantage trap resulting from resource endowments plunges resource-based regions into energy-intensive and carbon-intensive industries (Chiroleu-Assouline et al., 2020; Fu et al., 2016; Stijns, 2005; Yu et al., 2025), which not only contributes to more serious energy consumption and carbon emissions, but also restricts the transformation of industries towards decarbonization (Wang et al., 2019a).

3. Methodology and data

3.1. Non-radial directional distance function model

In view of the current energy and carbon emission constraints faced on a global scale, this paper refers to Zhang et al. (2014) and Lin and Du (2015) to measure the energy-carbon performance that reflects the maximization of real GDP while minimizing carbon emissions and energy consumption. We use labor, capital and energy as input factors, real GDP as desired output and CO_2 emissions as non-desired output.

The Data Envelope Analysis (DEA) method measures the gap between each decision unit and the production frontier boundary while considering both the promotion of GDP growth and the reduction of energy consumption as well as carbon emissions, thus measuring energy carbon performance. Traditional DEA methods generally employ the Shepard Distance Function (SDF) to measure efficiency, but the SDF's assumption that all inputs and outputs will change in the same proportion defeats the practical goal of increasing desired output while decreasing non-desired output. Chung et al. (1997) proposed the Directional Distance Function (DDF) to further refine the flawed assumption of SDF, and assumed that the increase in desired output is accompanied by a strictly equal proportional decrease in undesired output. Further, Zhou et al. (2012) argued that the assumption of DDF leads to a slack bias and proposed the Non-Radial Directional Distance Function (NDDF) model. NDDF model allows for a different proportion of desired output increases from non-desired output decreases, and thus measure energy environmental performance more accurately (Fukuyama & Weber, 2010).

Based on the NDDF model, this paper measures the energy carbon performance of Chinese cities by the DEA method. We take Capital (*C*), Labor (*L*), and Energy (*E*) as input factors, Real GDP (*Q*) as desired output, and Carbon emission (*C*) as undesired output. Where *L* is measured by average annual number of employees, *K* is the city's fixed asset stock calculated by Goldsmith's perpetual inventory method, *E* is measured by total annual electricity consumption, *Q* is the city's real GDP based on 2006, and *C* is carbon emission (Table 1).

Based on the above definitions of input and output variables, the specific production technologies in this paper are defined as follows.

$$T=\left\{(K,L,E,Q,C):(K,L,E),\,(Q,C)\right\}. \tag{1}$$

The above production technologies are described in the form of production sets as follows (Piscazo-Tadeo et al., 2005).

Table 1. Measurement indicators

	Variables	Description
Input variables	Labor (*L*)	Average annual number of employees
	Capital (*C*)	Measured by the perpetual inventory method, and the depreciation rate is set at 9.6%
	Energy (*E*)	Total annual electricity consumption
Output variables	Real GDP (*Q*)	Deflated nominal GDP based on 2006
	Carbon emission (*C*)	Measured by apparent fuel emissions

$$P(K,L,E)=\left\{(Q,C):(K,L,E,Q,C)\in T\right\}. \tag{2}$$

In order to make the energy-environmental performance comparable between periods, this paper uses global production techniques for measurement (Oh, 2010). We further assume that there are i = 1, 2, - - -, N decision making units (DUM) with a total of t = 1, 2, - - -, T periods. Accordingly, with constant returns to scale, the production technology Eq. (1) is expressed as follows.

$$T=\left\{\begin{array}{l}(K,L,E,Q,C):\sum_{t=1}^{T}\sum_{i=1}^{N}\lambda_{it}K_{it}\le K,\sum_{t=1}^{T}\sum_{i=1}^{N}\lambda_{it}L_{it}\le L\\ \sum_{t=1}^{T}\sum_{i=1}^{N}\lambda_{it}E_{it}\le E,\sum_{t=1}^{T}\sum_{i=1}^{N}\lambda_{it}Q_{it}\ge Q,\sum_{t=1}^{T}\sum_{i=1}^{N}\lambda_{it}C_{it}=C,\lambda_{it}\ge 0\end{array}\right\}. \tag{3}$$

Further, an NDDF for measuring the energy carbon performance of each DUM is set as follows.

$$\vec{D}(K,L,E,Q,C;g)=\sup\left\{w^{T}\beta:((K,L,E,Q,C)+g\bullet diag(\beta))\in T\right\}, \tag{4}$$

where, slack vector $\beta=(\beta_K,\beta_L,\beta_E,\beta_Q,\beta_C)^T\ge 0$ represents the change proportion of each input or output variable. $w=(w_K,w_L,w_E,w_Q,w_C)^T$ represents the weights of each input and output variable when measuring energy carbon performance, and it can be set flexibly according to the research purpose and content (Lin & Du, 2015). $g=(g_K,g_L,g_E,g_Q,g_C)$ is the direction vector and indicates the expansion direction of the desired output or the contraction direction of the input as well as undesired output. $diag(\beta)$ denotes the diagonalization of vector β.

It is reasonable to assume that inputs, desired outputs, and non-desired outputs matter equally, so they usually are weighted the same. However, substitutability among input factors makes the extent of energy savings or carbon reduction space difficult to capture (Lin & Du, 2015). Therefore, we set the weights of capital and labor to 0 when measuring energy carbon performance, which is reasonable in the studies that focus specifically on energy carbon performance (Lin & Du, 2015). Eventually, $w=\left(0,\ 0,\ \frac{1}{3},\frac{1}{3},\frac{1}{3}\right)^T$, and corresponds to the weight vector w, the direction vector is specified as $g=(0,0,-E,Q,-C)$. Under these assumptions, the above distance function can be solved by the following linear optimization procedure.

$$\vec{D}(K,L,E,Q,C)=\max\left\{\frac{1}{3}\beta_E+\frac{1}{3}\beta_Q+\frac{1}{3}\beta_C\right\}$$

$$\text{s.t.}\left\{\begin{array}{l}\sum_{t=1}^{T}\sum_{i=1}^{N}\lambda_{it}K_{it}\le K,\sum_{t=1}^{T}\sum_{i=1}^{N}\lambda_{it}L_{it}\le L,\sum_{t=1}^{T}\sum_{i=1}^{N}\lambda_{it}E_{it}\le E-\beta_E g\\ \sum_{t=1}^{T}\sum_{i=1}^{N}\lambda_{it}Q_{it}\ge Q+\beta_Q g_Q,\sum_{t=1}^{T}\sum_{i=1}^{N}\lambda_{it}C_{it}=C-\beta_C g_C\\ \lambda_{it}\ge 0,\beta_E,\beta_Q,\beta_C\ge 0\\ i=1,2\cdots,N,t=1,2\cdots,T\end{array}\right.. \tag{5}$$

By Eq. (5), we can obtain the optimal solution $\beta^*=(\beta_E^*,\beta_Q^*,\beta_C^*)^T$, $\beta_{E,it}^*$ represents the potential energy saving space of city i in year t, and $\beta_{Q,it}^*,\beta_{C,it}^*$ denote the potential GDP growth space and carbon emission reduction space of city i in year t, respectively. When $\beta^*_{s,it} = 0 (s = E,Q,C)$, then the city achieves optimal production on the corresponding input or output. Further, $\beta^*_{E,it} \times E_{it}$ represents the potential energy saving of city i in year t, and $\beta^*_{Q,it} \times Q_{it}$, $\beta^*_{C,it} \times C_{it}$ denote the potential GDP growth and total carbon emission reduction of city i in year t, respectively. In other words, if city i achieves optimal production in year t, its target values for energy input, GDP and carbon emissions are $E_{it} - \beta^*_{E,it} \times E_{it}$, $Q_{it} + \beta^*_{Q,it} \times Q_{it}$ and $C_{it} - \beta^*_{C,it} \times C_{it}$, respectively.

Energy consumption per unit of GDP and carbon emissions per unit of GDP are the core indicators of energy efficiency and carbon intensity respectively. Accordingly, we define Energy Performance (EP) and Carbon Performance (CP) respectively as follows.

$$EP_{it} = \frac{(E_{it} - \beta^*_{E,it} \times E_{it}) / (Q_{it} + \beta^*_{Q,it} \times Q_{it})}{E_{it} / Q_{it}}; \tag{6}$$

$$CP_{it} = \frac{(C_{it} - \beta^*_{C,it} \times C_{it}) / (Q_{it} + \beta^*_{Q,it} \times Q_{it})}{C_{it} / Q_{it}}. \tag{7}$$

EP_{it} represents the ratio between the target energy intensity and the actual energy intensity of city i in year t, and $0 \le EP_{it} \le 1$, a larger EP_{it} means better energy performance. CP_{it} denotes the ratio of target carbon emission intensity and actual carbon emission intensity of city i in year t, and $0 \le CP_{it} \le 1$, similarly, a larger CP_{it} means better carbon performance.

Finally, we weighted EP_{it} and CP_{it} to obtain the comprehensive indicator of Energy Carbon Performance (ECP). In performing the linear solution, we assign the same weight to energy inputs and carbon emissions. Therefore, it is more reasonable to set the weights of both EP_{it} and CP_{it} to 1/2 when calculating the ECP. The calculation formula for ECP is set as follows.

$$ECP_{it} = \frac{1}{2}\left[\frac{(E_{it} - \beta^*_{E,it} \times E_{it}) / (Q_{it} + \beta^*_{Q,it} \times Q_{it})}{E_{it} / Q_{it}} + \frac{(C_{it} - \beta^*_{C,it} \times C_{it}) / (Q_{it} + \beta^*_{Q,it} \times Q_{it})}{C_{it} / Q_{it}}\right]. \tag{8}$$

ECP_{it} is a comprehensive performance indicator that takes into account economic development, energy intensity and carbon intensity, and $0 \le ECP_{it} \le 1$, a larger ECP_{it} means better energy carbon performance. If ECP_{it} = 1, city i achieves optimal production.

3.2. Econometric model

3.2.1. Basic model

Based on Fixed Effect (FE) model, nonlinear model is constructed to estimate the impact of mineral resource dependence on energy carbon performance, which is set up as follows.

$$ecp_{it} = \alpha_0 + \alpha_1 mrd_{it} + \alpha_2 mrd^2_{it} + \alpha_3 control_{it} + \lambda_i + \theta_t + \varepsilon_{it}, \tag{9}$$

where, i represents city, t represents time, ecp denotes energy carbon performance, mrd and mrd^2 denote mineral resource dependence and the quadratic term of mineral resource dependence, respectively. $control$ represents the control variables. α_0 denotes the intercept term, α_1, α_2 and α_3 are coefficients, λ_i denotes urban fixed effects, θ_t denotes time fixed effects, ε_{it} denotes random error term.

3.2.2. Mechanism analysis model

Referring to Wang & Wang (2021), mechanism variables are used as dependent variables, to identify the mechanisms of energy carbon performance curse. The specific model is set as follows.

$$estru_{it} = \beta_0 + \beta_1 mrd + \beta_2 mrd^2 + \beta_3 control + \lambda_i + \theta_t + \varepsilon_{it}; \tag{10}$$

$$ecp_{it} = \varphi_0 + \varphi_1 \Delta estru_{it} + \varphi_2 control + \lambda_i + \theta_t + \varepsilon_{it}, \tag{11}$$

where *estru* is economic restructuring, including four dimensions of factor, human capital, energy and industrial restructuring. $\Delta estru$ denotes the quantitative change in economic structure induced by mineral resource dependence. β_0 and φ_0 are the intercept terms, β_1, β_2, β_3, φ_1, φ_2 and φ_3 are regression coefficients, and other symbols means the same as Equation (9).

3.3. Variables selection

3.3.1. Energy carbon performance

The dependent variable is energy carbon performance. We draw on Lin and Du (2015) and Zhang et al. (2014) to measure energy carbon performance by NDDF-DEA model, and finally obtain the performance through Eq. (8). Energy carbon performance is a comprehensive indicator that reflects both the minimization of energy consumption as well as carbon emissions and the maximization of real GDP, and a larger energy carbon performance value implies a better economic status. China's energy carbon performance has gradually increased between 2006 and 2019, and eastern cities generally achieve higher energy carbon performance (Figure 3).

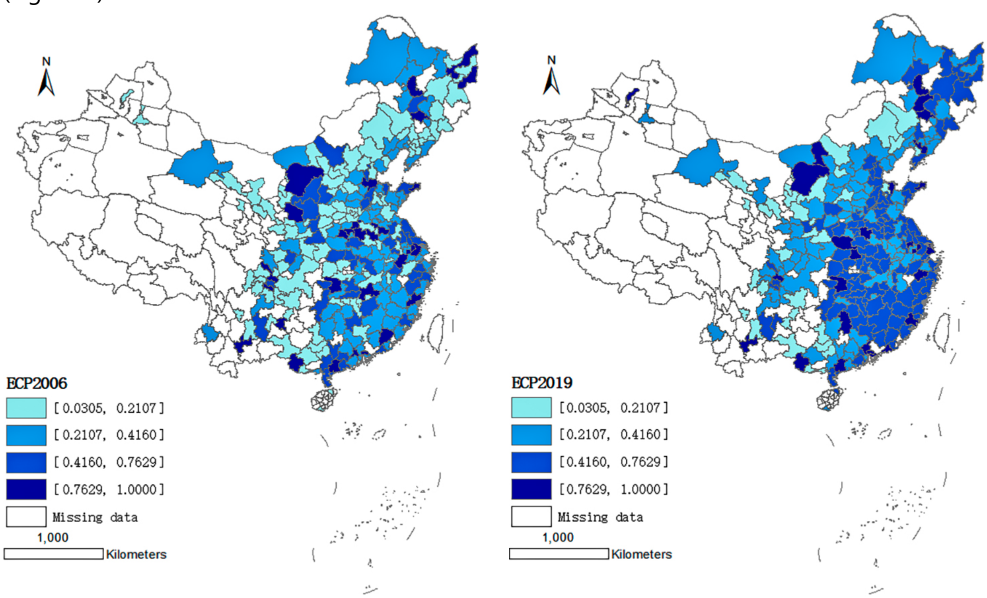

Figure 3. Spatial distribution of energy carbon performance in 2006 and 2019

3.3.2. Mineral resource dependence

The independent variable is mineral resource dependence. Within the theoretical framework of resource curse, the measurement of Natural Resource Abundance (NRA) or Natural Resource Dependence (NRD) has been discussed in detail by numerous scholars. Stijns (2005) pointed out that NRA and NRD are two concepts with inconsistent meanings. In more detail, NRA focuses primarily on the total amount of natural resources or the natural resources per capita, while NRD mainly focuses on the proportion of the scale of natural resource industries (number of employees and total output value) in the whole economy. Brunnschweiler and Bulte (2008) further argued that it is not the NRA but the NRD that is responsible for the resource curse and after all, the natural resources itself are the support for economic development. In conclusion, it is more reasonable that NRD is employed to examine the resource curse. As a mobile production factor, the allocation of labor across sectors can intuitively reflect regional resource endowments and the industrial structure characteristics derived from them. When the proportion of mining employees in a region is significantly higher than the national average, it indicates a high concentration of labor factors in the mineral resource sector, suggesting a high degree of dependence on natural resources in that region. Therefore, in this paper, the ratio of mining industry employees to total employees is used to characterize natural resource dependence, which is further defined as mineral resource dependence[2]. Compared to 2006, China's mineral resource dependence declined in 2019, and cities overly reliant on mineral resources mainly concentrated in Shanxi Province and China's northeast and west regions (Figure 4).

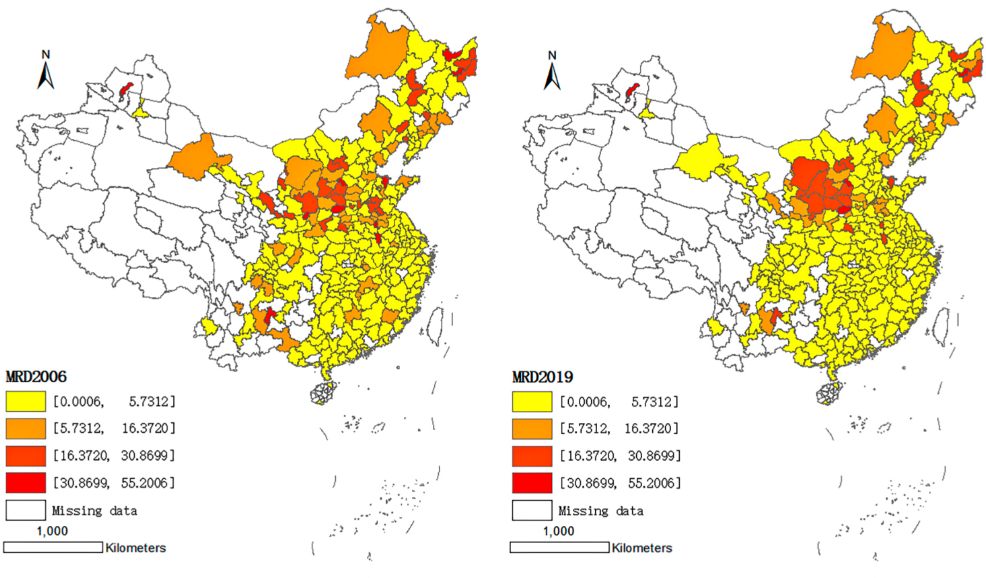

Figure 4. Spatial distribution of mineral resource dependence in 2006 and 2019

[2] According to the statistical caliber of *China Urban Statistical Yearbook*, the mining industry includes coal, oil and gas, ferrous metal, non-ferrous metal as well as other mining industries, while other natural resources such as forest resources are counted in the agricultural sector or other sectors.

3.3.3. Mechanism variables

The mechanism variable in this paper is economic restructuring. In this paper, economic restructuring is defined as a systematic indicator that integrates structural changes and evolution in various aspects of society. Combining the policy direction of China's economic restructuring in recent years and the goal of low-carbon transformation, we constructed an evaluation indicator system for economic restructuring from four dimensions: energy restructuring, factor restructuring, human capital restructuring and industry restructuring (Table 2), aiming to systematically reflect the development degree of economic restructuring in each city. We measured this indicator using the fully aligned polygon graphical index method (Wu et al., 2005). The core advantage of this method lies in its better adaptability to the collaborative and dynamic requirements of multi-dimensional adjustment of the economic structure. On the one hand, it does not require the presetting of subjective weights. Instead, it naturally reflects the contributions of adjustments to the energy structure, factor structure, human capital structure, and industrial structure through the side lengths of the polygon, effectively avoiding the flaw where advantageous dimensions overshadow the shortcomings (Zhang et al., 2022). On the other hand, by constructing multi-period polygon trajectories, this indicator can intuitively present the trend of adjustment and the time-lag differences among various structures, thereby reflecting the long-term dynamic evolution. Meanwhile, it quantifies the system balance degree through the ratio of the actual area to the area of an ideal regular polygon, which enables more accurate identification of the shortcomings that restrict the overall adjustment.

Table 2. Economic restructuring indicators system

Indicator		Variable	Unit
Economic restructuring	Energy restructuring	Ratio of clean energy consumption to total energy consumption	%
	Factor restructuring	Ratio of total capital stock to total labor force	10000 Yuan per person
	Human capital restructuring	Ratio of the number of college students to total population	%
	Industry restructuring	Industrial advancement index	–

Energy restructuring, factor restructuring and human capital restructuring are the fundamental drivers of economic restructuring. First, energy restructuring, an indicator employed to reflect the cleaner energy transition, is an important measure for protecting economic operation and promoting energy conservation as well as low-carbon development, and thus is an essential part of economic restructuring (Wang & Chang, 2014). The proportion of clean energy consumption in total energy consumption is used as a proxy variable for urban energy structure adjustment. Specifically, clean energy includes natural gas, hydropower, nuclear power, wind power, and solar energy. This indicator can reflect the status of urban clean energy transition. The larger the indicator value, the higher the degree of energy cleanliness.

Second, capital and labor are the basic factors for economic development, and factor allocation directly determines whether the economy reaches the optimal scale of production

(Galenson & Leibenstein, 1955). Therefore, optimizing factor input structure is also a necessary part of economic restructuring (Chen et al., 2013). The ratio of capital to labor is employed as a measure of factor restructuring which measures factor capitalization (Shao et al., 2022). Besides, economic restructuring also requires a corresponding adjustment of the internal structure within human capital (Fleisher et al., 2011). Finally, industry restructuring, measured by the industrial advancement index (Fu, 2010), is a key indicator in China's economic development policy and a core sign of China's economic restructuring. Compared with other parameters, the industrial advancement index not only captures the transformation of primary and secondary industries to tertiary industries, but also portrays the upgrading process of primary industries to secondary industries. Accordingly, the fully aligned polygon graphical index method is employed to quantify the economic restructuring in Chinese cities (Ren et al., 2022), and ultimately the economic restructuring is measured scientifically for each city during 2006–2019.

3.3.4. Control variables

To accurately identify the causal relationship between mineral resource dependence and energy carbon performance, we further control for variables such as government intervention, environmental regulation, energy prices, foreign direct investment, and institutional environment. Government intervention is measured by the ratio of government fiscal expenditure to GDP (Hao & Lu, 2018), environmental regulation is measured by the ratio the of number of words related to environmental protection to the total number of words in government reports by cities[3] (Chen et al., 2018; Kou & Han, 2021), energy prices are measured by the China coal price index, foreign direct investment is measured by the ratio of total actual use of foreign investment to GDP (You & Solomon, 2015), and institutional environment is measured by the urban marketization index (Li & Ramanathan, 2020).

Table 3. Statistical description of variables

Variable	Definition	Obs.	Mean	S.D.	Min	Max
ecp	Energy carbon performance	3710	0.396	0.255	0.031	1
ep	Energy performance	3710	0.401	0.260	0.028	1
cp	Carbon performance	3710	0.391	0.268	0.006	1
mrd	Mineral resource dependence	3710	5.612	9.410	0.000	57.823
estru	Economic restructuring	3710	0.201	0.149	0.006	0.728
gov	Government intervention	3710	17.205	8.305	4.265	148.516
er	Environmental regulation	3710	0.516	0.228	0.025	1.811
pri	Energy price	3710	153.768	25.807	101.47	196.04
fdi	Foreign direct investment	3710	0.282	0.284	0.000	2.990
inst	Institutional environment	3710	10.482	2.711	3.037	19.163

[3] The environmental-related terms used in this research include: environmental protection, pollution, energy consumption, emission reduction, emissions, ecology, green, low carbon, air, chemical oxygen demand, sulfur dioxide, carbon dioxide, PM10, and PM2.5.

3.4. Data source

Taking China's administrative divisions and missing data into account, we selected a sample of 265 cities in China from 2009–2019 for this study. The data are mainly from the China City Statistical Yearbook, China Statistical Yearbook, China City Construction Statistical Yearbook, National Bureau of Statistics, Wind database, provincial statistical yearbooks and prefecture-level municipal statistical bulletins. Also, to avoid estimation bias due to magnitudes, all variables are logged in the regression estimation, and the descriptive statistics are listed in Table 3.

4. Results and analysis

4.1. Energy carbon performance measurement results and analysis

4.1.1. Energy performance and carbon performance

According to Eqs. (6)–(7), we obtain the energy performance and carbon performance of Chinese cities. Figure 5 shows scatter plots of the average annual energy performance and carbon performance, which can show the preference for energy saving or emission reduction. To facilitate the comparison between them, we further introduce a diagonal line of $y = x$ as a reference. The point located below this diagonal line indicates that the city's carbon performance is superior to its energy performance. Out of 265 cities in China, 163 cities achieved higher energy performance than carbon performance, which means that in China energy performance outpaces carbon performance overall. The reason may lie in the fact that energy efficiency policies were given a larger priority before China's carbon reduction goals for carbon peak and carbon neutrality. Encouragingly, the scatter plot shows that as performance improves cities are gradually paying more attention on innovation in low-carbon technologies or carbon capture technologies, which will contribute to the achievement of China's carbon reduction goals.

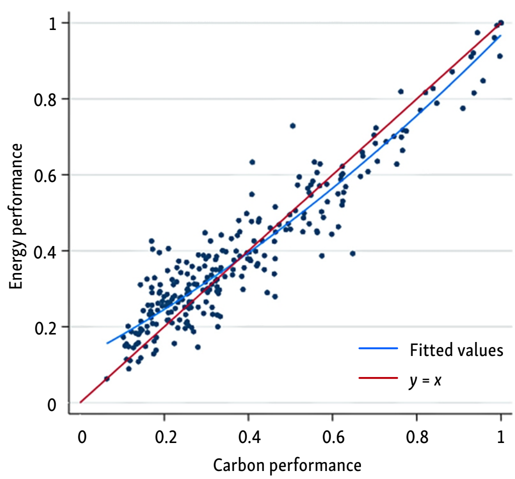

Figure 5. Performance scatter plot

4.1.2. Energy saving and carbon reduction

Each city's energy saving and carbon reduction are measured and summed in categories (Table 4). And we draw the following conclusions. (1) Without altering capital and labor inputs, there is enormous potential for energy saving and carbon reduction in China. Taking 2019 as an example, if all sample cities achieve optimal production, China could reduce electricity consumption by 2.734 trillion kWh and carbon emissions by 1.410 billion tons, accounting for 42.941% and 43.958% of total electricity consumption and carbon emissions, respectively. (2) Greater potential for energy saving and carbon emission reduction exists in RBC. In 2019, the potential reduction proportions of electricity consumption and carbon emissions in RBC are 46.860% and 48.452%, respectively, higher than the corresponding proportions of 41.457% and 42.393% in NRBC. (3) The potential energy saving and carbon emission reduction in China are decreasing year by year, and the gap between RBC and NRBC is decreasing year by year too.

Table 4. Energy saving and carbon emission reduction

Year	Resource-based cities				Non-resource-based cities			
	Energy saving ratio	Carbon reduction ratio	Energy saving	Carbon reduction	Energy saving ratio	Carbon reduction ratio	Energy saving	Carbon reduction
2006	71.406%	71.082%	2671.177	29228.421	64.663%	65.934%	7042.372	77919.635
2007	71.739%	71.373%	3037.389	34277.425	65.942%	66.762%	8063.444	90446.189
2008	70.577%	71.264%	3208.006	33919.327	64.309%	68.022%	8467.738	93477.863
2009	69.963%	71.442%	3373.002	34281.115	59.616%	64.237%	8229.874	90095.390
2010	67.946%	69.147%	3778.758	37049.580	57.884%	63.005%	9071.715	94234.012
2011	67.454%	68.796%	4046.420	37363.694	55.483%	60.980%	9459.648	90714.039
2012	67.609%	68.760%	4107.659	37987.993	57.562%	62.677%	10399.423	100497.115
2013	63.812%	63.710%	4144.053	37874.711	56.351%	55.244%	10910.056	95512.808
2014	65.224%	64.135%	4522.860	39799.500	60.325%	54.426%	11984.239	96850.737
2015	58.011%	56.893%	3758.577	38349.749	57.623%	50.009%	11981.524	88577.540
2016	59.269%	56.865%	4078.122	39993.740	58.812%	49.420%	13338.250	91476.364
2017	48.276%	51.235%	7062.802	37884.138	41.750%	43.101%	16709.304	84674.905
2018	48.381%	46.779%	7742.196	39718.970	40.922%	40.247%	17890.558	84382.090
2019	46.860%	48.452%	8124.625	40144.064	41.475%	42.393%	19217.448	100865.309

Note: The units of energy saving and carbon emission reduction are billion kWh and 10,000 tons respectively.

4.2. Regression results and analysis

4.2.1. Basic regression results and analysis

The regression results of mineral resource dependence on energy carbon performance are listed in Table 5. Compared to OLS and RE models, FE models can further avoid partial estimation bias caused by unobservable variables that do not vary over time. Therefore, regression results based on the FE model are used to explain the effects of mineral resource dependence on energy carbon performance. According to the results in columns (7)–(9), the regression coefficients of the quadratic term of mineral resource dependence on energy carbon performance, energy performance, and carbon performance are –0.005, –0.004, and –0.005, respectively, all significantly negative at least at the 10% level. This confirms the existence of an inverted U-shaped relationship between mineral resource dependence and energy carbon performance, meaning that in the initial stage of development, mineral resource dependence can effectively improve urban energy carbon performance, but when mineral resource dependence reaches a certain intensity, it exerts a negative impact on urban energy carbon performance. In other words, the energy carbon performance curse does not completely negate the role of mineral resource development as a driver of economic development. To verify this, a scatter plot of mineral resource dependence versus energy carbon performance is drawn in this paper (as shown in Figure 6). This is because in the initial stage of mineral resource development, it can effectively reduce raw material costs, accelerate the urban industrialization process, and improve the economic output per unit of energy input. In this case, the positive "resource dividend" dominates. However, as the degree of mineral resource dependence increases, urban development gradually forms path dependence and structural rigidity, with production factors excessively concentrated in resource-intensive sectors, causing cities to fall into the "resource curse", which in turn inhibits energy carbon performance.

Table 5. Basic regression results

Variable	OLS			RE			FE		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ecp	*ep*	*cp*	*ecp*	*ep*	*cp*	*ecp*	*ep*	*cp*
mrd	–0.049***	–0.044***	–0.053***	–0.051***	–0.049***	–0.047***	–0.031***	–0.024*	–0.040***
	(–9.745)	(–8.505)	(–9.953)	(–5.524)	(–4.900)	(–4.776)	(–2.656)	(–1.805)	(–3.256)
mrd^2	–0.002	–0.001	–0.002	–0.005***	–0.005**	–0.005**	–0.005**	–0.004*	–0.005**
	(–1.140)	(–0.503)	(–1.618)	(–3.082)	(–2.538)	(–2.542)	(–2.502)	(–1.940)	(–2.455)
gov	–0.130***	–0.133***	–0.151***	0.105***	0.019	0.184***	0.134***	0.036	0.223***
	(–4.849)	(–4.802)	(–5.212)	(2.948)	(0.472)	(4.852)	(3.200)	(0.744)	(5.046)
er	0.010	–0.019	0.031	–0.039**	–0.044**	–0.038**	–0.049***	–0.050**	–0.050***
	(0.443)	(–0.802)	(1.249)	(–2.411)	(–2.365)	(–2.245)	(–2.852)	(–2.571)	(–2.789)
pri	0.129**	0.227***	0.039	0.035	0.128***	–0.044	0.605***	0.882***	0.163
	(2.204)	(3.765)	(0.622)	(1.063)	(3.375)	(–1.253)	(3.557)	(4.536)	(0.910)
fdi	–0.016**	–0.007	–0.018**	–0.012*	–0.011	–0.003	–0.011*	–0.007	–0.012*
	(–2.297)	(–0.926)	(–2.432)	(–1.936)	(–1.601)	(–0.484)	(–1.702)	(–0.949)	(–1.777)
inst	0.378***	0.414***	0.301***	0.449***	0.553***	0.265***	0.041	0.083	–0.011
	(8.998)	(9.583)	(6.665)	(10.379)	(11.442)	(5.798)	(0.421)	(0.747)	(–0.107)
cons	–2.302***	–2.871***	–1.638***	–2.649***	–3.116***	–2.067***	–4.566***	–5.721***	–2.626***
	(–7.783)	(–9.458)	(–5.155)	(–15.482)	(–16.006)	(–11.477)	(–7.351)	(–8.060)	(–4.009)
Time fixed effect	NO	NO	NO	NO	NO	NO	YES	YES	YES
City fixed effect	NO	NO	NO	NO	NO	NO	YES	YES	YES
R-sq	0.071	0.071	0.059	0.047	0.057	0.022	0.160	0.150	0.096
N	3710	3710	3710	3710	3710	3710	3710	3710	3710

Note: *** proves significance at 1% level, ** proves significance at 5% level, * proves significance at 10% levels. The z-value is put in (), and the p-value is put in []. And all of these are the same as the tables below.

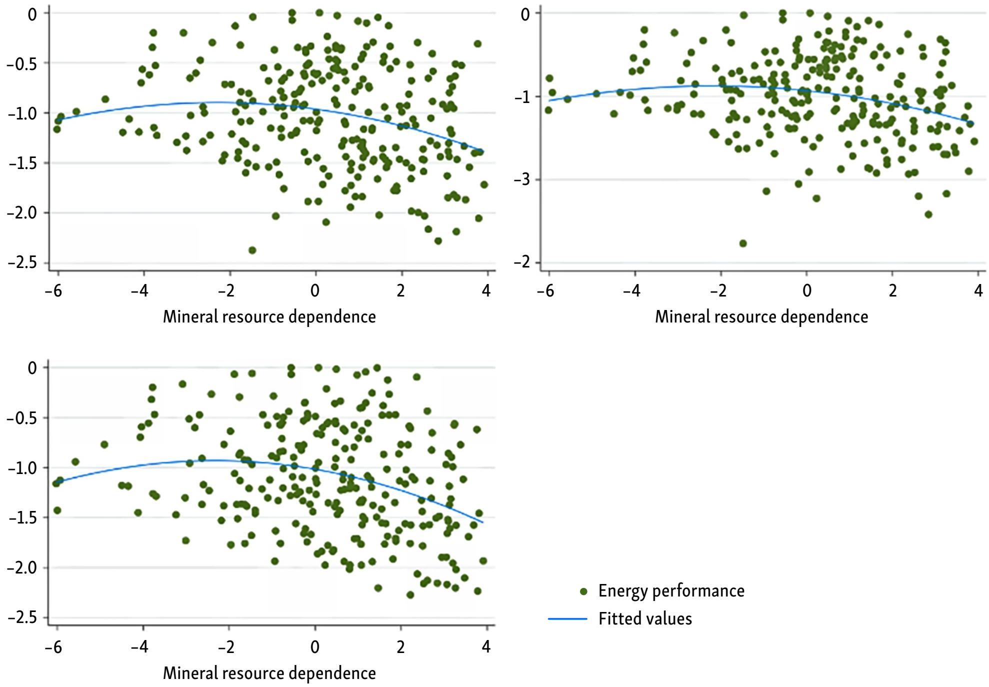

Figure 6. Scatter plot between mineral resource dependence and ECP, EP as well as CP

Based on the basic regression results, we further ascertain the inflection point of the inverted U-shaped relationship by the U test proposed by Lind and Mehlum (2010). According to the U test results, the inflection point occurs when *mrd* = 0.042%. This implies that when mineral resource dependence is less than 0.042%, mineral resources exploitation performs as the resource blessing, but when it exceeds 0.042%, the mineral resources exploitation serves as a curse on energy carbon performance. Accordingly, 208 of China's 265 cities had a mineral resource dependence greater than 0.042% in 2019, which implies that most Chinese cities are trapped in the energy carbon performance curse. Meanwhile, the inflection points of the U-shaped relationship between mineral resource dependence and energy performance as well as carbon performance occur at *mrd* = 0.062% and *mrd* = 0.019%, respectively, which suggests that mineral resource dependence more likely to trigger the carbon performance curse. The reason may lie in the fact that innovation in low carbon technologies and carbon capture technologies is more easily neglected than that in energy-saving technologies. And Figure 7 illustrates that the number of cities blessed by mineral resources in China is rising, which indicates that China's efforts to save energy and reduce carbon emissions are paying off.

4.2.2. Endogeneity treatment

Mineral resource dependence can affect energy carbon performance by influencing resource consumption and low carbon technology innovation. In turn, the improvement in energy carbon performance driven by GDP growth can lead to a greater demand for mineral resources. Besides, our model may not capture all the variables that would affect both energy carbon

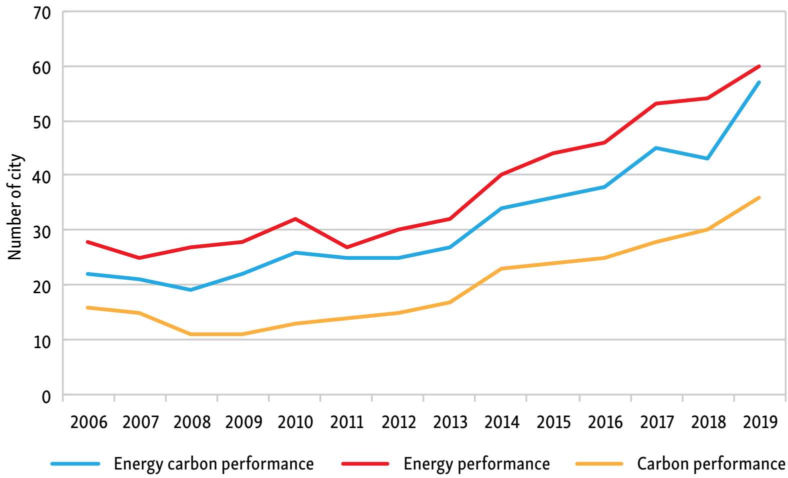

Figure 7. Number of resource-blessed cities in China

performance and mineral resource dependence, which will lead to estimation bias. Therefore, the IV is employed in this paper to address the endogeneity.

The urban precipitation from 1991–2004 and the average urban slope are adopted as our instrumental variables. As instrumental variables, historical rainfall 15 years ago satisfies the requirements of correlation and exogeneity. On the one hand, urban rainfall determines the water content in underground rock formations, and the water content will increase the difficulty for mining construction and the probability of mining accidents, which may directly affect the mining decision of enterprises. This means that rainfall 15 years ago can have an impact on current mineral resource dependence by influencing historical mining decisions[4]. On the other hand, historical rainfall as a natural variable itself satisfies the exogeneity requirement, and rainfall 15 years ago can hardly influence energy carbon performance through other channels. Urban slope directly affects the difficulty of mining and thus is considered an essential factor in the economic valuation of mines, which implies that the urban slope satisfies the correlation requirement of instrumental variable. Moreover, urban slope as a geographical variable itself satisfies the exogeneity requirement of instrumental variables. In conclusion, it is rational that urban slope and precipitation 15 years ago are adopted as the instrumental variables in this paper.

The regression results based on the instrumental variables method are listed in Table 6. As shown in the results of column (2), mineral resource dependence is negatively correlated with urban precipitation from 1991 to 2004 and positively correlated with the average urban slope, which is consistent with the expected results. On the one hand, urban rainfall determines the water content of underground rock formations and the flow of water systems. Richer groundwater flow and higher rock formation water content will increase the probability of mining accidents. Once a mining accident occurs, the consequences are extremely serious, so enterprises are more likely to choose not to mine, and the degree of urban natural resource

[4] According to the relevant Chinese laws, the mine's life span ranges from 10 to 30 years.

dependence will decrease. On the other hand, for resource-based cities, the greater the urban slope, the higher the difficulty of mining. Extracting the same amount of resources requires more employees, so the proportion of employees in the mining industry in the city will be higher, which means a greater degree of natural resource dependence. The F-statistic in the first stage regression is 56.994, much larger than the empirical value of 10, which rejects the original hypothesis of weak instrumental variables. And according to the results in columns (4), (8) and (12), we notice that the regression coefficients of mineral resource dependence and its quadratic term are still significantly negative compared to the regression results of the OLS model. In conclusion, the conclusion that the energy carbon performance curse does exist still holds after dealing with endogeneity.

Table 6. Regression results of IV

Variable		ECP				EP				CP			
		OLS	2SLS			OLS	2SLS			OLS	2SLS		
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		ecp	*mrd*	*mrd*^{2}	*ecp*	*ep*	*mrd*	*mrd*^{2}	*ep*	*cp*	*mrd*	*mrd*^{2}	*cp*
mrd		–0.046*** (–9.197)			–0.187*** (–11.050)	–0.040*** (–7.795)			–0.144*** (–8.530)	–0.053*** (–9.807)			–0.238*** (–12.690)
mrd^2		–0.002 (–1.377)			–0.006 (–0.637)	–0.001 (–0.747)			0.008 (0.929)	–0.003* (–1.833)			–0.022** (–2.230)
rain			–1.291*** (–21.340)	0.867*** (3.920)			–1.291*** (–21.340)	0.867*** (3.920)			–1.291*** (–21.340)	0.867*** (3.920)	
slope			0.626*** (9.650)	–2.659*** (–11.210)			0.626*** (9.650)	–2.659*** (–11.210)			0.626*** (9.650)	–2.659*** (–11.210)	
control		YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
cons		–5.511*** (–7.970)	19.833*** (7.990)	–19.026** (–2.100)	–4.214*** (–5.320)	–7.066*** (–9.998)	19.833*** (7.990)	–19.026** (–2.100)	–5.842*** (–7.380)	–3.115*** (–4.170)	19.833*** (7.990)	–19.026** (–2.100)	–1.720* (–1.950)
N		3710	3710	3710	3710	3710	3710	3710	3710	3710	3710	3710	3710
Partial R-sq	*lnmrd*		0.108				0.108				0.108		
	lnmrd^2		0.032				0.032				0.032		
Minimum eigenvalue			56.994				56.994				56.994		

4.2.3. Robustness tests

Based on the FE model, several robustness tests are employed to examine the validity of findings. First, we exclude the possible interference of control variables to the conclusions by adding them step by step, and the empirical results are listed in Table A1 (Appendix) due to the article space limitation. Second, four municipalities – Beijing, Shanghai, Tianjin and Chongqing – are excluded to avoid the influence of differences in China's administrative divisions. Third, considering the fact that the public health event COVID-19 might exert an impact on both energy carbon performance and mineral resource dependence, this study excluded the sample in 2019 to avoid estimation bias due to this epidemic. Finally, to avoid the bias by outliers, we replace ECPs and mineral resource dependencies that are smaller than the 1st quartile with the 1st quartile while replacing that are larger than the 99th quartile with the 99th quartile. The empirical results of robustness tests are presented in Table 7. All robustness tests show that mineral resource dependence significantly inhibits urban energy carbon performance, which proves that our conclusions are robust.

Table 7. Regression results of the robustness tests

Variable	Excluding municipalities			Avoiding COVID-19			Outlier treatment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ecp	ep	cp	ecp	ep	cp	ecp	ep	cp
mrd	–0.033***	–0.026*	–0.042***	–0.035***	–0.028**	–0.043***	–0.030**	–0.023*	–0.038***
	(–2.799)	(–1.933)	(–3.383)	(–2.860)	(–2.040)	(–3.446)	(–2.550)	(–1.710)	(–3.100)
mrd^2	–0.005**	–0.004**	–0.005**	–0.005***	–0.005**	–0.006***	–0.005**	–0.004*	–0.005**
	(–2.544)	(–1.969)	(–2.497)	(–2.585)	(–2.005)	(–2.702)	(–2.280)	(–1.780)	(–2.160)
gov	0.145***	0.052	0.228***	0.092**	0.043	0.133***	0.136***	0.036	0.226***
	(3.441)	(1.070)	(5.122)	(2.057)	(0.848)	(2.847)	(3.260)	(0.760)	(5.180)
er	–0.050***	–0.052***	–0.051***	–0.040**	–0.044**	–0.039**	–0.049***	–0.051***	–0.049***
	(–2.897)	(–2.640)	(–2.789)	(–2.357)	(–2.292)	(–2.199)	(–2.860)	(–2.640)	(–2.750)
pri	0.526***	0.782***	0.109	0.621***	0.818***	0.272*	0.617***	0.927***	0.118
	(3.068)	(3.992)	(0.601)	(3.922)	(4.568)	(1.655)	(3.650)	(4.780)	(0.670)
fdi	–0.012*	–0.008	–0.013*	0.001	0.005	–0.001	–0.011*	–0.007	–0.011*
	(–1.824)	(–1.077)	(–1.862)	(0.195)	(0.644)	(–0.126)	(–1.680)	(–0.990)	(–1.650)
inst	0.064	0.111	0.006	0.129	0.156	0.102	0.028	0.049	0.023
	(0.658)	(0.995)	(0.059)	(1.289)	(1.386)	(0.986)	(0.290)	(0.440)	(0.230)
cons	–4.263***	–5.344***	–2.410***	–4.672***	–5.550***	–3.093***	–4.595***	–5.863***	–2.482***
	(–6.803)	(–7.464)	(–3.644)	(–8.294)	(–8.717)	(–5.288)	(–7.440)	(–8.280)	(–3.840)
Time fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES
R-sq	0.155	0.143	0.094	0.160	0.149	0.104	0.161	0.149	0.098
N	3654	3654	3654	3445	3445	3445	3710	3710	3710

4.2.4. Heterogeneity analysis

1. Resource endowment heterogeneity

Based on the full-sample regression results we conclude that the energy carbon performance curse does exist, and to further confirm this conclusion, we divide the sample into RBC and NRBC for group estimation. According to the results in columns (1)–(3) of Table 8, the absolute values of regression coefficients of mineral resource dependence in RBC are larger than those in the full sample regressions at higher significance levels. The results in columns (4)–(6) indicate that the regression coefficient of mineral resources dependence on carbon performance is negative but insignificant in NRBC, and that the regression coefficients on energy carbon performance and energy performance are both positive. This implies that the energy carbon performance curse mainly exists in RBC rather than in NRBC. The pronounced energy-carbon performance curse in RBC stems from the combined effects of the core mechanisms of the resource curse and distorted factor allocation. From the perspective of resource curse theory, the industrial structure of RBC is deeply entrenched in resource dependency lock-in. Production factors such as capital and labor are excessively concentrated in high-energy-consumption, high-carbon-emission resource extraction and primary processing stages, crowding out efficient allocation directions like energy-saving technology R&D and low-carbon industry cultivation. The factor substitution effect further exacerbates this issue. The low-cost advantage of local resources distorts price signals, making the short-term cost of increased energy input for enterprises far lower than the cost of technological innovation for carbon reduction. Under rational choice, this leads to path dependence characterized by high consumption and low efficiency. Consequently, RBC consistently exhibit low energy utilization efficiency and weak carbon reduction outcomes, resulting in a significantly stronger energy-carbon performance curse compared to NRBC. In fact, the mineral resource dependence in NRBC is concentrated at a level close to zero. While most RBC are overly dependent on mineral resources (Figure 8). Therefore, it is an expected and logical result that resource-based cities suffer from a more serious energy carbon performance curse than non-resource-based cities. In conclusion, the regression results in Table 8 further support the conclusion that the energy carbon performance curse does exist.

Table 8. Regression results for resource endowment heterogeneity

Variable	Resource-based cities			Non-resource-based cities		
	(1)	(2)	(3)	(4)	(5)	(6)
	ecp	*ep*	*cp*	*ecp*	*ep*	*cp*
mrd	–0.074***	–0.074***	–0.071***	0.004	0.019	–0.015
	(–3.449)	(–3.114)	(–3.123)	(0.323)	(1.158)	(–0.999)
mrd^2	–0.016**	–0.019***	–0.012*	0.002	0.004	0.000
	(–2.554)	(–2.629)	(–1.718)	(0.935)	(1.507)	(0.094)
gov	0.194***	0.170**	0.227***	0.049	–0.111*	0.187***
	(2.721)	(2.130)	(3.005)	(0.950)	(–1.865)	(3.470)
er	–0.027	–0.024	–0.029	–0.059***	–0.065***	–0.060***
	(–0.905)	(–0.721)	(–0.900)	(–2.940)	(–2.763)	(–2.833)
pri	0.470	0.603*	0.309	0.871***	1.256***	0.221
	(1.560)	(1.787)	(0.965)	(4.276)	(5.318)	(1.028)
fdi	–0.036***	–0.037***	–0.030***	0.014	0.024**	0.005
	(–3.675)	(–3.342)	(–2.857)	(1.623)	(2.344)	(0.495)
inst	0.123	0.158	–0.019	–0.115	–0.072	–0.095
	(0.743)	(0.857)	(–0.106)	(–0.956)	(–0.515)	(–0.747)
cons	–4.275***	–4.902***	–3.364***	–5.170***	–6.693***	–2.538***
	(–3.803)	(–3.891)	(–2.818)	(–7.070)	(–7.885)	(–3.288)
Time fixed effect	YES	YES	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES	YES	YES
R-sq	0.218	0.208	0.133	0.135	0.130	0.080
N	1456	1456	1456	2254	2254	2254

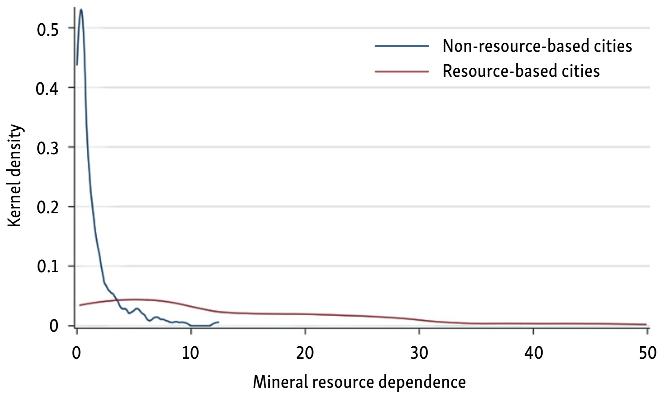

Figure 8. Kernel density of mineral resource dependence

2. Air pollution heterogeneity

All samples are divided into polluted and non-polluted cities based on the annual average good air quality rate of each city from 2015–2019 for group regression[5]. A city is defined as non-polluted city when its good air quality rate is greater than the median good air quality rate of the sample, and as polluted city when the opposite is true. In columns (1)–(3) of Table 9, the absolute values of regression coefficients of mineral resource dependence on energy carbon performance, energy performance and carbon performance in polluted cities are all larger than those in the full sample regression. While the regression results in non-polluted cities show that there is no energy carbon performance curse, and even in terms of energy performance, mineral resources serve as a significant blessing, which indicates that polluted cities should be treated with more attention when we explore the path to promote low carbon transition.

Table 9. Regression results of air pollution heterogeneity

Variable	Polluted cities			Non-polluted cities		
	(1)	(2)	(3)	(4)	(5)	(6)
	ecp	*ep*	*cp*	*ecp*	*ep*	*cp*
mrd	–0.070***	–0.074***	–0.069***	0.012	0.033*	–0.011
	(–4.614)	(–4.130)	(–4.463)	(0.647)	(1.650)	(–0.548)
mrd^2	–0.008***	–0.009***	–0.008**	0.000	0.002	–0.001
	(–2.862)	(–2.638)	(–2.468)	(0.156)	(0.807)	(–0.335)
gov	0.114*	–0.044	0.267***	0.195***	0.134**	0.244***
	(1.826)	(–0.595)	(4.143)	(3.429)	(2.124)	(3.983)
er	–0.057**	–0.061**	–0.050**	–0.040*	–0.039	–0.049*
	(–2.368)	(–2.156)	(–2.033)	(–1.652)	(–1.446)	(–1.880)
pri	0.612***	0.980***	–0.009	0.471*	0.678**	0.189
	(2.656)	(3.614)	(–0.039)	(1.876)	(2.429)	(0.698)

[5] Good air quality rate = total number of days with air quality level 2 or above in the year/365*100%.

End of Table 9

Variable	Polluted cities			Non-polluted cities		
	(1)	(2)	(3)	(4)	(5)	(6)
	ecp	*ep*	*cp*	*ecp*	*ep*	*cp*
fdi	–0.027***	–0.015	–0.040***	–0.006	–0.004	–0.002
	(–2.622)	(–1.242)	(–3.810)	(–0.663)	(–0.477)	(–0.204)
inst	0.107	0.097	0.158	0.031	0.132	–0.137
	(0.810)	(0.627)	(1.171)	(0.215)	(0.828)	(–0.884)
cons	–4.697***	–5.997***	–2.317***	–4.067***	–5.146***	–2.514**
	(–5.582)	(–6.053)	(–2.682)	(–4.452)	(–5.060)	(–2.552)
Time fixed effect	YES	YES	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES	YES	YES
R-sq	0.225	0.196	0.155	0.123	0.126	0.074
N	1848	1848	1848	1862	1862	1862

5. Mechanism analysis

5.1. Economic restructuring

Based on the analysis results of resource endowment heterogeneity, we find that the "resource curse" effect of mineral resource dependence on energy carbon performance only exists in RBC and is not significant in NRBC. To accurately analyze the specific mechanism by which mineral resource dependence affects energy carbon performance, this paper conducts mechanism analysis using the sample of RBC. First, we examine the transmission path of the energy carbon performance curse from the perspective of economic restructuring. Column (1) of Table 10 reports the regression results of mineral resource dependence on the mechanism variable of restructuring. The results show that the regression coefficient of mineral resource dependence on restructuring is –0.032, which is significant at the 10% level. The regression coefficient of the quadratic term of mineral resource dependence on economic restructuring is –0.011, which is significant at the 5% level. This indicates that in the short term, mineral resource development promotes economic structure adjustment. However, excessive mineral resource dependence makes cities more likely to fall into the comparative advantage trap, thereby having a significant negative impact on economic restructuring. Columns (2)–(4) respectively report the regression results of the economic restructuring caused by mineral resource dependence on urban energy carbon performance, energy performance, and carbon performance. The results show that the regression coefficients of the economic restructuring caused by mineral resource dependence on urban energy carbon performance, energy performance, and carbon performance are 1.788, 1.929, and 1.510 respectively, all significant at the 1% level. This indicates that the lower the degree of economic restructuring, the worse the urban energy carbon performance, energy performance, and carbon performance. Overall, the stickiness of economic restructuring solidifies the structures of energy, factors, industries, and human capital, hinders the transformation of high-energy-consuming industries and the application of low-carbon technologies, leads to low energy utilization efficiency, and thus reduces urban energy carbon performance, energy performance, and carbon performance.

Table 10. Results of the mechanism analysis for economic restructuring

Variable	(1)	(2)	(3)	(4)
	estru	*ecp*	*ep*	*er*
mrd	–0.032*			
	(–1.879)			
mrd^2	–0.011**			
	(–2.258)			
Δestru		1.788***	1.929***	1.510***
		(4.099)	(3.947)	(3.258)
gov	–0.002	0.196***	0.173**	0.228***
	(–0.033)	(2.753)	(2.166)	(3.023)
er	0.132***	–0.263***	–0.279***	–0.228***
	(5.512)	(–3.931)	(–3.718)	(–3.206)
pri	1.506***	–2.210***	–2.292***	–1.946**
	(6.314)	(–2.882)	(–2.668)	(–2.390)
fdi	–0.009	–0.019*	–0.019	–0.016
	(–1.202)	(–1.868)	(–1.611)	(–1.433)
inst	0.474***	–0.723***	–0.754***	–0.731***
	(3.627)	(–2.851)	(–2.657)	(–2.715)
cons	–10.362***	14.177***	15.028***	12.174**
	(–11.632)	(2.886)	(2.731)	(2.333)
Time fixed effect	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES
R-sq	0.657	0.217	0.207	0.132
N	1456	1456	1456	1456

5.2. Energy restructuring

Column (1) of Table 11 reports the regression results of mineral resource dependence on the mechanism variable of energy restructuring. The results show that the regression coefficient of mineral resource dependence on energy restructuring is –0.010, significant at the 5% level, and the regression coefficient of the quadratic term of mineral resource dependence on energy restructuring is –0.004, significant at the 1% level. This indicates that in the short term, resource rents generated by mineral resource development can provide critical financial support for energy restructuring. However, when a city becomes overly dependent on mineral resources, the low costs and energy consumption stickiness caused by energy endowments such as coal and oil hinder the use of clean energy, exerting a significant negative impact on energy restructuring. Columns (2)–(4) report the regression results of energy restructuring caused by mineral resource dependence on urban carbon energy performance, energy performance, and carbon performance, respectively. The regression coefficients are 5.125, 5.553, and 4.285, all significant at the 1% level, indicating that the lower the degree of energy restructuring, the worse the urban carbon energy performance, energy performance, and carbon performance. Overall, the stickiness of energy restructuring exacerbates path dependence on fossil fuels, which hinders the improvement of urban energy efficiency and thus reduces energy carbon performance, energy performance, and carbon performance.

Table 11. Results of the mechanism analysis for energy restructuring

Variable	(1)	(2)	(3)	(4)
	en	ecp	ep	er
mrd	–0.010**			
	(–2.335)			
mrd^2	–0.004***			
	(–3.170)			
Δ*en*		5.125***	5.553***	4.285***
		(4.027)	(3.895)	(3.171)
gov	0.029**	0.045	0.009	0.102
	(2.002)	(0.542)	(0.094)	(1.167)
er	0.014**	–0.100***	–0.103**	–0.090**
	(2.326)	(–2.753)	(–2.536)	(–2.321)
pri	–0.274***	1.895***	2.142***	1.509***
	(–4.491)	(4.496)	(4.536)	(3.371)
fdi	–0.005**	–0.010	–0.009	–0.008
	(–2.543)	(–0.900)	(–0.686)	(–0.684)
inst	0.080**	–0.285	–0.284	–0.358*
	(2.391)	(–1.529)	(–1.359)	(–1.811)
cons	1.230***	–10.694***	–11.828***	–8.781***
	(5.397)	(–6.303)	(–6.224)	(–4.873)
Time fixed effect	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES
R-sq	0.133	0.217	0.207	0.132
N	1456	1456	1456	1456

5.3. Factor restructuring

Table 12, column (1) reports the regression results of mineral resource dependence on factor restructuring as the mechanism variable. The results show that the regression coefficient of mineral resource dependence on factor restructuring is –0.027, significant at the 1% level. Abundant mineral resources lead to a large amount of capital and labor factors being locked in primary production sectors, while crowding out investment and labor in other industries, exerting a significantly negative impact on urban factor restructuring. Columns (2)–(4) report the regression results of factor restructuring caused by mineral resource dependence on urban energy carbon performance, energy performance, and carbon performance, respectively. The results show that the regression coefficients of factor restructuring caused by mineral resource dependence on urban energy carbon performance, energy performance, and carbon performance are 1.708, 1.628, and 1.816, respectively, all significant at least at the 10% level. This indicates that the lower the degree of factor restructuring, the worse the urban energy carbon performance, energy performance, and carbon performance. When production factors such as capital and labor are difficult to transfer from high-carbon sectors to clean sectors, the energy allocation efficiency of the economic system will remain low, thereby inhibiting energy carbon performance, energy performance, and carbon performance.

Table 12. Results of the mechanism analysis for factor restructuring

Variable	(1)	(2)	(3)	(4)
	fac	*ecp*	*ep*	*er*
mrd	–0.027***			
	(–3.216)			
mrd^2	0.003			
	(1.177)			
Δ*fac*		1.708**	1.628*	1.816**
		(2.290)	(1.948)	(2.297)
gov	–0.270***	0.672***	0.628***	0.731***
	(–9.745)	(3.153)	(2.631)	(3.236)
er	0.053***	–0.111**	–0.103*	–0.120**
	(4.558)	(–2.194)	(–1.817)	(–2.235)
pri	3.594***	–5.517**	–5.079*	–6.096**
	(30.703)	(–2.023)	(–1.663)	(–2.110)
fdi	0.014***	–0.058***	–0.058***	–0.054***
	(3.747)	(–4.053)	(–3.578)	(–3.538)
inst	0.185***	–0.243	–0.198	–0.394*
	(2.887)	(–1.137)	(–0.826)	(–1.739)
cons	–14.928***	20.408*	18.496	23.093*
	(–34.151)	(1.798)	(1.455)	(1.920)
Time fixed effect	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES
R-sq	0.942	0.211	0.200	0.129
N	1456	1456	1456	1456

5.4. Industrial restructuring

Column (1) of Table 13 reports the regression results of mineral resource dependence on the mechanism variable of industrial restructuring. The results show that the regression coefficient of mineral resource dependence on industrial restructuring is –0.002, significant at the 10% level, and the regression coefficient of the quadratic term of mineral resource dependence on industrial restructuring is –0.001, significant at the 1% level. This indicates that in the short term, the capital accumulation from mineral resource development enables rapid expansion of the industrial sector, driving the economy to transform from a traditional agricultural-dominated structure to a modern one with increased shares of industry and services. In the long term, abundant mineral resources tend to lead to an industrial layout dominated by heavy chemical industries, gradually forming a single industrial development path. This results in cities with higher mineral resource dependence having a lower proportion of the tertiary industry and greater industrial structure stickiness. Columns (2)–(4) report the regression results of industrial restructuring caused by mineral resource dependence on urban energy carbon performance, energy performance, and carbon performance, respectively. The regression coefficients are 31.646, 34.334, and 26.381, all significant at the 1% level, indicating that the lower the degree of industrial restructuring, the worse the urban energy carbon performance, energy performance, and carbon performance. The stickiness of industrial restructuring makes it difficult for resource-based cities to escape the pattern dominated by the secondary industry, whose energy intensity and carbon intensity are significantly higher than those of the tertiary industry. This leads to persistently low energy efficiency, ultimately inhibiting urban energy carbon performance, energy performance, and carbon performance.

Table 13. Results of the mechanism analysis for industrial restructuring

Variable	(1)	(2)	(3)	(4)
	indu	*ecp*	*ep*	*er*
mrd	–0.002*			
	(–1.883)			
mrd^2	–0.001***			
	(–2.656)			
Δ*indu*		31.646***	34.334***	26.381***
		(4.002)	(3.877)	(3.141)
gov	–0.006**	0.378***	0.370***	0.381***
	(–2.089)	(4.596)	(4.018)	(4.355)
er	0.005***	–0.191***	–0.202***	–0.165***
	(4.351)	(–3.627)	(–3.425)	(–2.954)
pri	0.136***	–3.816***	–4.053***	–3.255***
	(11.471)	(–3.278)	(–3.108)	(–2.633)
fdi	0.000	–0.041***	–0.042***	–0.034***
	(0.421)	(–4.158)	(–3.810)	(–3.243)
inst	–0.007	0.337*	0.391**	0.161
	(–1.034)	(1.899)	(1.965)	(0.855)
cons	1.243***	–43.757***	–47.707***	–36.330***
	(28.049)	(–4.543)	(–4.422)	(–3.551)
Time fixed effect	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES
R-sq	0.680	0.217	0.207	0.132
N	1456	1456	1456	1456

5.5. Human capital restructuring

Table 14, column (1) reports the regression results of mineral resource dependence on human capital restructuring as the mechanism variable. The results show that the regression coefficient of mineral resource dependence on human capital restructuring is 0.038, but this positive effect is not significant. The possible reason lies in that mineral resources in China are owned by local governments, and the fiscal revenue generated from mineral resource development serves as an important source of funding for public education in China. Mineral resource endowments have a positive effect on regional human capital improvement. Therefore, the mechanism by which mineral resource dependence inhibits energy carbon performance by hindering human capital upgrading is not verified.

Table 14. Results of the mechanism analysis for human capital restructuring

Variable	(1)	(2)	(3)	(4)
	hum	*ecp*	*ep*	*er*
mrd	0.038			
	(1.476)			
mrd^2	0.004			
	(0.586)			
Δ*hum*		–2.157***	–2.247***	–1.959***
		(–4.078)	(–3.792)	(–3.489)
gov	–0.280***	–0.406**	–0.454**	–0.319*
	(–3.266)	(–2.425)	(–2.420)	(–1.797)
er	0.100***	0.190***	0.203***	0.168***
	(2.765)	(3.209)	(3.051)	(2.673)
pri	1.584***	3.901***	4.182***	3.418***
	(4.374)	(4.635)	(4.434)	(3.826)
fdi	–0.020*	–0.078***	–0.080***	–0.068***
	(–1.672)	(–5.377)	(–4.942)	(–4.421)
inst	0.143	0.422**	0.467**	0.258
	(0.722)	(2.269)	(2.244)	(1.308)
cons	–7.725***	–21.010***	–22.360***	–18.528***
	(–5.711)	(–5.296)	(–5.030)	(–4.400)
Time fixed effect	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES
R-sq	0.178	0.217	0.206	0.133
N	1456	1456	1456	1456

6. Conclusions

Based on the environmental perspective, this paper extends the traditional resource curse to the energy carbon performance curse. We find that in 2019, China could reduce electricity consumption by 2.734 trillion kWh and carbon emissions by 1.410 billion tons if optimal production is achieved in all sample cities, which respectively account for 42.941% and 43.958% of total electricity consumption and total carbon emissions, which hints to the governments that compared with current optimal production, there is still a huge potential room for cities to optimize their environmental performance.

Through nonlinear econometric models, we identify an inverted U-shaped relationship between natural resources and energy carbon performance. Through nonlinear econometric models, we identify an inverted U-shaped relationship between natural resources and energy carbon performance. Mineral resource dependence below 0.042% contributes to economic growth and environmental performance, however, when it is above 0.042%, greater mineral resource dependence means a more severe energy carbon performance curse. And most Chinese cities' resource dependence are above 0.042%. Accordingly, this study argues that the controversy between resource curse and resource blessing may only result from differences in the samples distributed on different sides of the inverted U-shaped relationship.

Against the backdrop of China's high-quality transformational development, this research concentrates on the core pathway of economic restructuring stickiness to examine the impact of natural resource dependence on energy carbon performance and its underlying mechanisms. The research finds that natural resources slow down the process of economic restructuring in resource-based cities, leading to lower energy carbon performance. Further, energy, factor and industry restructuring stickiness get verified as the specific path for the above mechanism. Based on the above conclusions, the following policy recommendations are put forward.

First, implement differentiated regulatory approaches for cities with varying degrees of mineral resource dependency. For cities where resource dependency remains below the inflection point, the focus should be on securing resource dividends. Policy guidance should be provided to prioritise the allocation of resource revenues towards low-carbon technology reserves and industrial diversification, thereby avoiding premature path dependency. For cities where dependence has already surpassed the tipping point, the core challenge lies in overcoming the resource curse. Aiming to mitigate energy-carbon performance losses, these cities should establish phased plans to reduce resource dependency. Concurrently, a dynamic monitoring mechanism should be implemented to regularly assess regulatory effectiveness and refine policy instruments.

Second, targeted policies should be employed to overcome adjustment inertia across different dimensions, thereby clearing structural obstacles for the low-carbon transition. In the energy dimension, efforts should be made to shift the energy consumption structure towards cleaner sources, using policy incentives to increase the share of clean energy and break the path lock-in of fossil fuel dependency. In the factor dimension, efforts should be made to optimize the allocation of capital and labour between resource-intensive and non-resource-intensive sectors, refine cross-sectoral factor mobility mechanisms, and reduce excessive concentration of production factors in resource-intensive industries. In the industry dimension, efforts should be made to accelerate industrial upgrading, cultivate high-value-added, low-carbon non-resource industries, and reduce the economic system's dependence on resource-based industries.

Third, refine fiscal and tax support policies by granting tax incentives and financial subsidies to low-carbon transition projects in resource-based cities, thereby mitigating short-term economic losses during structural adjustment. Furthermore, enhance regional coordination mechanisms to foster collaboration between resource-based cities and regions leading in low-carbon development, enabling the adoption of advanced practices alongside the introduction of technology, capital and talent resources. Concurrently, it is recommended that energy carbon performance indicators be incorporated into local government assessment frameworks, thereby guiding local authorities to prioritise structural adjustment and low-carbon development.

However, the energy carbon performance hypothesis still leaves some directions that worth researching in the future. First, technological factors are not sufficiently considered. Although we have discussed low-carbon technologies through decomposition regressions of energy-carbon performance, technological progress as well as technological efficiency have been neglected in this research, which is important for economic growth and low-carbon development. Second, some indicators such as energy restructuring or factor restructuring could be more accurate constrained by the data availability. Third, the theoretical models on the energy carbon performance curse hypothesis can be further explored.

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Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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APPENDIX

Table A.1 Regression results of robustness tests

Variable	Energy carbon performanc						Energy performanc						Carbon performance					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	ecp	*ecp*	*ecp*	*ecp*	*ecp*	*ecp*	*ep*	*ep*	*ep*	*ep*	*ep*	*ep*	*cp*	*cp*	*cp*	*cp*	*cp*	*cp*
mrd	–0.030**	–0.029**	–0.030***	–0.030***	–0.031***	–0.031***	–0.022*	–0.022*	–0.023*	–0.023*	–0.024*	–0.024*	–0.039***	–0.038***	–0.040***	–0.040***	–0.040***	–0.040***
	(–2.561)	(–2.493)	(–2.623)	(–2.623)	(–2.644)	(–2.656)	(–1.674)	(–1.654)	(–1.772)	(–1.772)	(–1.783)	(–1.805)	(–3.211)	(–3.112)	(–3.239)	(–3.239)	(–3.261)	(–3.256)
mrd^2	–0.005**	–0.005**	–0.005**	–0.005**	–0.005**	–0.005**	–0.004*	–0.004*	–0.004*	–0.004*	–0.004**	–0.004*	–0.005**	–0.005**	–0.005**	–0.005**	–0.005**	–0.005**
	(–2.361)	(–2.321)	(–2.492)	(–2.492)	(–2.516)	(–2.502)	(–1.806)	(–1.794)	(–1.949)	(–1.949)	(–1.963)	(–1.940)	(–2.319)	(–2.261)	(–2.428)	(–2.428)	(–2.453)	(–2.455)
gov		0.142***	0.139***	0.139***	0.135***	0.134***		0.044	0.040	0.040	0.038	0.036		0.230***	0.227***	0.227***	0.223***	0.223***
		(3.399)	(3.313)	(3.313)	(3.230)	(3.200)		(0.915)	(0.835)	(0.835)	(0.788)	(0.744)		(5.219)	(5.135)	(5.135)	(5.049)	(5.046)
er			–0.048***	–0.048***	–0.049***	–0.049***			–0.050**	–0.050**	–0.050**	–0.050**			–0.049***	–0.049***	–0.050***	–0.050***
			(–2.806)	(–2.806)	(–2.851)	(–2.852)			(–2.545)	(–2.545)	(–2.570)	(–2.571)			(–2.744)	(–2.744)	(–2.790)	(–2.789)
pri				0.680***	0.665***	0.605***				1.013***	1.003***	0.882***				0.164*	0.147	0.163
				(7.265)	(7.072)	(3.557)				(9.471)	(9.334)	(4.536)				(1.658)	(1.484)	(0.910)
fdi					–0.011*	–0.011*					–0.007	–0.007					–0.012*	–0.012*
					(–1.740)	(–1.702)					(–1.010)	(–0.949)					(–1.774)	(–1.777)
inst						0.041						0.083						–0.011
						(0.421)						(0.747)						(–0.107)
cons	–1.289***	–1.628***	–1.679***	–4.822***	–4.765***	–4.566***	–1.324***	–1.428***	–1.481***	–6.162***	–6.124***	–5.721***	–1.276***	–1.825***	–1.877***	–2.633***	–2.572***	–2.626***
	(–52.813)	(–15.857)	(–16.119)	(–11.999)	(–11.822)	(–7.351)	(–47.580)	(–12.182)	(–12.449)	(–13.422)	(–13.296)	(–8.060)	(–49.488)	(–16.861)	(–17.097)	(–6.215)	(–6.053)	(–4.009)
Time effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster level	City	City	City	City	City	City	City	City	City	City	City	City	City	City	City	City	City	City
R-sq	0.155	0.157	0.159	0.159	0.160	0.160	0.147	0.147	0.149	0.149	0.150	0.150	0.086	0.093	0.095	0.095	0.096	0.096
N	3710	3710	3710	3710	3710	3710	3710	3710	3710	3710	3710	3710	3710	3710	3710	3710	3710	3710