STUDY ON THE IMPACT OF ENVIRONMENTAL REGULATIONS AND THE DIGITAL ECONOMY ON CIRCULAR ECONOMY EFFICIENCY IN THE CONTEXT OF CARBON NEUTRALITY FROM 2009-2023 IN CHINA

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(Received 3rd Oct 2025; accepted 2nd Jan 2026)

Abstract. This study measures regional circular economy efficiency (CEE) and examines its impact factors of environmental regulations and the digital economy from 2009-2023 in China, yielding the following conclusions: (1) At the national level, environmental regulations exhibit a U-shaped relationship with CEE, initially suppressing it before promoting it. Regionally, the coefficient for the first order term and the coefficient for the second order term of environmental regulation intensity in the central and western regions fail to pass the significance test. In the eastern region, environmental regulations first reduce CEE before enhancing it, confirming a U-shaped relationship. (2) Digital economy can promote CEE in whole regions except western region which is not significant. (3) Economic development can improve CEE in all regions except western region. The industrial structure inhibit CEE in all regions, though the negative impact in the eastern region is not statistically significant. Foreign trade enhances CEE in the eastern region but has a negligible effect in the central and western regions. The impact of resource endowments on CEE is insignificant in national and eastern. However, technological advancements in central and western regions have boosted efficiency in the mining sector, thereby elevating the average energy efficiency of resource rich areas.
Keywords: *high quality economic development, sustainable development, environmental economy, digital technology, low-carbon development*

Introduction

With economic development and deepening industrialization, the spread and escalation of environmental issues worldwide have given rise to global, integrated, and cumulative ecological challenges. These pose significant obstacles to Earth’s ecosystems and human survival, directly impacting global sustainable development and the harmonious relationship between humanity and the environment (Ferreira, 2025). In pursuit of more sustainable development models that foster harmony between humanity and nature, nations have begun reevaluating the drawbacks of extensive economic growth patterns and their detrimental impacts on human habitats (Muhirwa et al., 2025). Developed countries have progressively introduced and published national strategic documents, actively exploring well designed policy frameworks to guide sustainable development (Agunsoye et al., 2025). The circular economy guided by the principles of “reduction, reuse, and recycling,” and characterized by “low consumption, low emissions, and high efficiency,” encompasses not only economic growth but also emphasizes comprehensive resource utilization and zero environmental pollution. It represents a novel economic development paradigm aligned with sustainable development principles (Quinto et al., 2025; Rudenko et al., 2025; Sesay et al., 2025). CEE refers to the

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17011722

quantitative relationship between inputs and outputs in a circular economy. It represents the ratio of operational outcomes to operational costs, constituting a quantitative study of circular economy performance from an efficiency perspective. CEE comprehensively reflects the level of circular economy development, resource conservation, and environmental friendliness (Lei et al., 2025; Niu et al., 2025). Therefore, evaluating and analyzing CEE provides a holistic assessment of its developmental status, making quantitative research on this metric practically significant.

Against the backdrop of a burgeoning new technological revolution, the digital economy has emerged as a pivotal force driving the transformation of the global economic structure (Bressanelli et al., 2018; Zhou et al., 2021). China's digital economy has experienced rapid growth. The rapid development of the digital economy demonstrates robust vitality and boundless potential, driving profound transformations in production methods, lifestyles, and governance approaches. Its characteristics—high technology, high growth, and high cleanliness—create new opportunities for achieving a high-quality green, low-carbon circular economy. Digital technology serves as a vital means and key enabler for achieving carbon peaking and carbon neutrality. On one hand, digital tools can be leveraged to build a green, low-carbon, and circular economic system, improve production processes, optimize production technologies, phase out outdated high-carbon production capacity, and green social productivity. On the other hand, they can also promote the embedded concepts of simplicity, moderation, and green, low-carbon living inherent in digital development, expand green consumption demand, and drive the greening and decarbonization of social production methods, creating a mutually reinforcing relationship between ecological environmental protection and economic and social development. Against this backdrop, how to leverage the development of the digital economy to propel urban economies toward new models of green, low carbon, circular development is an urgent and important issue requiring clarification. Implementing a circular economy involves not only material flows but also information flows. Coordinating these flows is essential for circular economic development. The digital technologies empower circular economy industries, can enhance efficiency, innovate business models, and unlock immense value and potential for circular economic growth, with a pronounced multiplier effect (Cagno et al., 2025). Actively promoting the integrated development of the digital and circular economies represents an effective pathway for advancing high quality economic development.

Due to increasingly severe resource shortages and the emergence of environmental pollution issues, various environmental regulatory measures have emerged and continued to evolve. Following the reform and opening up, the state introduced a series of environmental governance policies and laws and regulations, marking the entry of environmental regulation into a phase of legalization. Environmental regulation not only strengthened the sense of responsibility among administrative departments but also established different norms and restrictions for enterprises and individuals, demonstrating the state's determination to govern environmental pollution and conserve resources. Due to regional development disparities, differences in the types and implementation intensity of environmental regulations are objectively present, and their effectiveness varies. Nevertheless, they have all effectively restricted local industrial enterprises' pollution emissions and resource consumption, consequently increasing corporate costs. Enterprises aiming to maximize profits will adjust their production plans accordingly, directly impacting CEE (Agovino et al., 2024). Against this backdrop, this study examines the impact mechanisms of environmental regulations and the digital economy

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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on circular economy efficiency using panel data from 30 provinces spanning 2009 to 2023. scientifically analyzing whether environmental regulations and the digital economy promote or inhibit local circular economy development. This research provides reference for regional governments to adjust the intensity of environmental regulation implementation based on local conditions and formulate coordinated development policies for the digital economy and regional circular economies. It also offers strategic recommendations for enterprises on operating green circular economy models, improving local environmental conditions, and enhancing economic efficiency. Therefore, this topic holds practical significance for enhancing China's circular economy efficiency and promoting high-quality economic development.

Literature review

Efficiency measurement in the circular economy

The concept of the circular economy refers to economic activities that adhere to ecological principles during economic development, integrating ecodesign, resource utilization, clean production, and sustainable consumption to achieve harmonious development between economic systems and natural systems. Zhu et al. (2013) proposed that the circular economy represents a new closed-loop economic development model capable of minimizing impacts on nature.

Data Envelopment Analysis (DEA) serves as the primary method for evaluating CEE, with the C2R model (Constant Returns to Scale model), Malmquist model, and super-efficiency DEA model being widely adopted. Cao et al. (2013) applied DEA evaluation to determine CEE values across Chinese provinces. Through comparative analysis and argumentation, they identified key efficiency related factors, concluding that overall domestic CEE maintains a fluctuating upward trend. Regionally, eastern provinces demonstrate the strongest and most balanced development, while western regions exhibit significant developmental disparities. Jia et al. (2014) restructured the DEA model to incorporate nondesired outputs, evaluating CEE in China's construction sector. Using data from 2002 to 2012, they found that technical efficiency alone was insufficient to determine the development level of the construction industry's circular economy. Nie and Wang (2022) developed a two stage DEA model tailored to industrial circular economy characteristics, incorporating nondesirable outputs and exogenous inputs. Using the Malmquist index method, they analyzed the efficiency of industrial circular economy in Southwest China from 2016 to 2019 from both static and dynamic perspectives. The study indicates that the overall development of industrial circular economy in the Southwest region is positive, with the gap narrowing gradually compared to more industrialized regions. Li et al. (2017) employed DEA and Malmquist productivity index models to measure the comprehensive CEE and subefficiency in technology, scale, and economy for China's 30 provinces from 2003 to 2012. They examined the temporal characteristics and spatial differentiation of this efficiency, proposing the causes and influencing factors behind the spatial variation in CEE.

Research on the spatial and temporal evolution of circular economy efficiency

Vanbruggen and Zonneveld (2022) propose that digital technologies can monitor material and information flows in the "reduce, reuse, recycle" aspects of circular economy, thereby enhancing its efficiency. Pagoropoulos et al. (2017) contend that integrating digital technologies throughout the entire circular economy process significantly elevates its development level. Domestic scholars Chen et al. (2023) observed that China's provincial level digital economy and circular economy achieved "leapfrog growth" in coupling coordination, yet regional development remains highly uneven, persisting in an east strong, west weak pattern. Liang and Xu (2024) found that the digital economy can elevate the level of green, low carbon circular economies. Additionally, some scholars argue that the digital economy can guide green economic development by improving capital allocation and boosting green total factor productivity (2021); restrict the growth space for high emission industries, alleviate environmental pollution, and drive green industrial restructuring (Li and Zhou, 2021; Han et al., 2022); promote green technological innovation and industrial upgrading, mitigate information asymmetry, thereby reducing carbon emissions (Guo et al., 2022), and ultimately advance circular economic development.

Research on the impact of environmental regulations on regional circular economy efficiency

Environmental regulations constitute a form of societal regulatory action. Given the external diseconomies inherent in environmental pollution, governments must implement corresponding policies and measures to guide and control corporate behavior, thereby achieving coordinated environmental and economic development. Although Porter and Van der Linde (1995) argued that stringent environmental regulations can stimulate corporate innovation, enhance resource utilization efficiency, and boost productivity. Consequently, the increased revenue generated by enterprises may offset or even exceed the compliance costs incurred under environmental regulations. However, this win-win hypothesis has faced rigorous criticism from neoclassical economists. Scholars have also reached inconsistent conclusions, Rehfeld et al. (2007) found that environmental regulations positively influence ecoproduct innovation in the chemical and pharmaceutical industries but have negligible effects on the food and beverage sector. Li and Cao (2017) discovered that government environmental regulation exhibits a statistically significant U-shaped impact on circular economy performance in China's central and western regions. Third, the intensity of environmental regulation formed by industrial enterprises' pollution control investments exhibits a statistically significant U-shaped effect across eastern, central, and western regions. Li (2022) utilizing panel data from 18 urban agglomerations between 2011 and 2019 and combining entropy analysis with the coupling coordination degree model, explored the coupling coordination mechanism and level among industrial ecologization, circular economy performance, and environmental regulation within urban agglomerations. The findings reveal that the coupling coordination level of the industrial ecologization circular economy performance environmental regulation system is relatively high in eastern urban agglomerations, while northeastern and western regions exhibit lower coupling coordination. Wang and Feng (2018) demonstrate that energy saving and emission reduction environmental regulations exhibit complementary effects in enhancing circular economy performance, with water pollution indicators showing a more pronounced complementary effect than air pollution indicators.

We can find that the essence of the circular economy lies in guiding economic activities according to ecological principles. It advocates the reuse of waste through advanced circular technologies and industrial chain technologies, emphasizing the recycling and reuse of material resources. This represents a new sustainable economic model. In quantitative research, foreign studies focus on evaluating regional circular

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17011722

economy levels through ecological efficiency assessments, primarily employing material flow analysis methods. Domestic quantitative research concentrates on evaluating regional circular economy levels, employing methods such as the Analytic Hierarchy Process (AHP), Principal Component Analysis (PCA), Fuzzy Decision Making, and Grey Relational Analysis. For assessing CEE, the DEA model is predominantly used. While these findings provide valuable insights for studying CEE, the development of circular economies is influenced by external environmental factors such as natural conditions and economic development levels. Differences in external environments lead to variations in regional circular economy models and directly impact input output efficiency. Methodologically, existing literature predominantly employs traditional DEA models to evaluate regional CEE. This approach treats environmental variables, random errors, inputs, and outputs as an integrated whole when calculating efficiency values. Consequently, the derived efficiency figures incorporate the influence of environmental variables and random errors, failing to accurately reflect the true state of regional circular economy development. This study complements existing research by integrating the super-efficiency SBM (Slacks-Based Measure) model with regional CEE measurement. Furthermore, research on the relationship between the digital economy and the circular economy remains limited, offering significant scope for exploration. By incorporating environmental regulations and the digital economy into a unified framework to examine their combined impact on CEE, this work provides theoretical insights for scholars worldwide and offers valuable references for policy formulation.

Methodology

Circular economy efficiency measurement methods

Model construction

The DEA models proposed by Charnes and Cooper (1978) and Charnes and Banker (1984) are the most widely applied in numerous contexts. The DEA method avoids the subjective determination of output relationships among input factors by humans, reducing the subjective bias present in previous methods (Charnes et al., 1989). With the continuous innovation and perfection of research methods, the technical system of efficiency measurement has undergone significant paradigm evolution. DEA is a key method for measuring efficiency among similar decision units. The classical DEA model under constant returns to scale is termed the CCR (Charnes, Cooper and Rhodes) model; the model under variable returns to scale incorporates the constraint $\Sigma\lambda = 1$ and is termed the BCC (Banker-Charnes-Cooper) model. Both CCR and BCC models operate on the principle of maximizing output while minimizing inputs. In actual production processes, substantial pollutants such as wastewater, sulfur dioxide, and industrial solid waste are generated—referred to as undesirable outputs. In practice, minimizing undesirable outputs enhances efficiency, which contradicts the output maximization principle of traditional CCR and BCC models. The angularity and radial properties of these models constrain them to scaling inputs and outputs proportionally at the same angle, failing to adequately address slack issues in inputs and outputs. This limitation introduces inaccuracies in the relative efficiency evaluations of traditional models. Tone (2001) proposed the DEA-SBM model, which incorporates slack variables into the objective function. Using the difference variable as the measurement basis, it yields efficiency values ranging from 0 to 1. The model formula is as follows:

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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$$\begin{cases} min\theta = \frac{1+\frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{ik}}{1-\frac{1}{q}\sum_{r=1}^{q} s_r^+ / y_{rk}} \\ \sum_{j=1,j\neq k}^{n} x_{ij}\lambda_i + s_i^- = x_{ik} \\ \sum_{j=1,j\neq k}^{n} x_{rj}\lambda_i - s_r^+ = y_{rk} \\ \lambda_j, s^+, s^- \geq 0 \\ i = 1,2,\cdots,m; r = 1,2,\cdots,q; j = 1,2,\cdots,n(j \neq k) \end{cases} \quad \text{(Eq.1)}$$

θ Efficiency measurement value of the decision-making unit
m Input indicator quantity
s^- Input slack variable
x_{ik} Input indicator
q Number of output indicators
s^+ Output slack variables
y_{rk} Output indicators
λ Constraints
n Number of decision units

The traditional DEA model cannot address the issue of “nondesired outputs,” which can be handled using the DEA-SBM model. The advantage of the SBM model lies in its unit invariance, meaning the efficiency scores measured by the DEA-SBM model are unaffected by the units of input and output indicators. Since the efficiency scores measured by the SBM model range between 0 and 1, and all efficient decision units have an efficiency score of 1, direct comparison and ranking among them cannot be achieved. Therefore, Tone (2002) improved the DEA-SBM model by proposing the Super-SBM model. This model can measure the super-efficiency values of decision units, enable further comparison and rank of efficient decision units—that is, the efficiency values of these decision units can potentially exceed 1.

Compared to traditional DEA models—CCR (the original DEA model) and BCC (a CCR model with variable returns to scale)—the Super-SBM model simultaneously resolves issues of slack variables and radial input output problems. Moreover, super-efficient SBM achieves a breakthrough in addressing the inability to precisely rank efficiency values when multiple decision units are efficient. The Super-SBM model formula can be expressed as:

$$\begin{cases} min\theta = \frac{1+\frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{ik}}{1-\frac{1}{q}\sum_{r=1}^{q} s_r^+ / y_{rk}} \\ \sum_{j=1,j\neq k}^{n} x_{ij}\lambda_i - s_i^- \leq x_{ik} \\ \sum_{j=1,j\neq k}^{n} x_{rj}\lambda_i + s_r^+ \geq y_{rk} \\ \lambda_j, s^+, s^- \geq 0 \\ i = 1,2,\cdots,m; r = 1,2,\cdots,q; j = 1,2,\cdots,n(j \neq k) \end{cases} \quad \text{(Eq.2)}$$

If $\theta < 1$, and either $S{-}{\neq}0$ or $S + {\neq}0$, it indicates that the decision unit has not achieved optimal efficiency. If $\theta \geq 1$, and either $S + = 0$ or $S - = 0$, the decision unit achieves maximum efficiency. A larger θ value indicates a higher relative efficiency rate for the decision unit, signifying greater effectiveness.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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Building upon the existing Super-SBM model, Tone further incorporated nondesirable outputs into the Super-SBM framework. This paper adopts the Super-SBM model that accounts for nondesirable outputs, whose formulation is as follows:

$$\begin{cases} min\theta = \dfrac{1+\frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{ik}}{1-\frac{1}{q_1+q_2}(\sum_{r=1}^{q_1}\frac{s_r^+}{y_{rk}}+\sum_{t=1}^{q_2} s_t^{b-}/b_{rk})} \\ \sum_{j=1,j\neq k}^{n} x_{ij}\lambda_i - s_i^- \leq x_{ik} \\ \sum_{j=1,j\neq k}^{n} x_{rj}\lambda_i + s_r^+ \geq y_{rk} \\ \lambda_j, s^+, s^- \geq 0 \\ i = 1,2,\cdots,m; r = 1,2,\cdots,q; j = 1,2,\cdots,n(j \neq k) \end{cases} \tag{Eq.3}$$

In the equation: $q1$ is the quantity of desired output indicators, $q2$ is the quantity of undesired output indicators, s_t^{b-} is the slack variable for undesired outputs, and the objective function $\theta$is strictly decreasing with respect to s_i^-, s_r^+, and s_t^{b-}. Solving the above equation allows calculation of the efficiency value for nonexpected outputs. When a region exhibits a CEE value greater than 1, it indicates that the region's input output relationship is relatively efficient compared to other decision units, and thus no adjustments to input or output indicators are required. Conversely, when a region's CEE value is less than 1, it indicates that the region's input output relationship is relatively inefficient. Both input and output indicators require optimization, with the slack representing the level of optimization needed for these indicators. By adjusting the various input and output indicators, the CEE of the region can be enhanced.

Input output indicator system

In selecting specific input and output indicators for the circular economy, this paper comprehensively references the national circular economy evaluation indicator system and evaluation indicators distilled from relevant Chinese circular economy research literature. Four input indicators and seven output indicators were chosen to evaluate CEE. The relationship between CEE input indicators and output indicators is shown in *Table 1*.

Table 1. *Input output indicator system*

Indicator type	Indicator name	Unit
Input indicators	Energy consumption per unit of GDP	kWh/10,000 yuan
	Energy intensity per unit of GDP	Tons of standard coal equivalent/10,000 yuan
	Special investment in industrial emission control	10,000 yuan
	Water consumption per unit of GDP	m^3/10,000 yuan
Expected Output	Per capita GDP	Ten thousand yuan
	Industrial wastewater compliance rate	%
	Green coverage rate	%
	Value of comprehensive utilization of solid, liquid, and gaseous wastes	Ten thousand yuan
Nonexpected output	Industrial wastewater discharge volume	m^3
	Industrial SO_2 emissions	μg/m^3
	Industrial dust emissions	mg/m^3

GDP (gross domestic product), SO_2 (sulfur dioxide)

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Regression model specification

In analyzing the dynamic effects of the digital economy and environmental regulations on regional circular economies, this study employs annual panel data in China spanning 2009 to 2023 to construct a dynamic panel model, given data availability. The sample data exhibits both time series and cross-sectional characteristics. Compared to static panel models, the concurrently employed dynamic GMM panel model accommodates dynamic effects while mitigating endogeneity issues arising from lagged terms (Wang and Lv, 2025). As an effective dynamic panel data analysis, GMM can effectively solve the phenomenon of inconsistent parameter estimation, and has superior performance. It can solve the endogenesis, individual effect, autocorrelation and heteroscedasticity of panel variables, and does not need accurate distribution information of disturbance terms, allowing random error terms to have serial correlation and heteroscedasticity (Liu and Yin, 2025). The fundamental representation of the dynamic panel data model is:

$$Y_{i,t} = \alpha Y_{i,t-1} + \beta X_{i,t} + \mu_i + \varepsilon_{i,t}, i = 1,2.\cdots, N; t = 1,2,\cdots, T \qquad \text{(Eq.4)}$$

here, $Y_{i,t-1}$ represents the lagged term of $Y_{i,t}$, while μ_i denotes the fixed effect for individual i. The coexistence of the lagged first order term $Y_{i,t-1}$ of the dependent variable $Y_{i,t}$ and the fixed effect $\mu_i$constitutes the distinctive feature of dynamic panel data. If the fixed effect is omitted, the regression equation takes the following form:

$$Y_{i,t} = \alpha Y_{i,t-1} + \beta X_{i,t} + \varepsilon_{i,t} \qquad \text{(Eq.5)}$$

At this point, regression analysis using either OLS or a random effects (RE) model can be employed. If the lagged first order term $\alpha Y_{i,t-1}$ of the dependent variable $Y_{i,t}$ is removed, the regression equation takes the following form:

$$Y_{i,t} = \beta X_{i,t} + \mu_i + \varepsilon_{i,t} \qquad \text{(Eq.6)}$$

For this model, a fixed effects (FE) model analysis is sufficient. Therefore, the panel data model in this study is:

$$CEE_{i,t} = \alpha_0 + \alpha_1 CEE_{i,t-1} + \alpha_2 DE_{i,t} + \alpha_3 ER_{i,t} + \beta \sum_{j=1}^{n} X_{i,t} + \gamma_t + \theta_i + \mu_i + \varepsilon_{i,t} \qquad \text{(Eq.7)}$$

Here, i denotes region and t denotes time; α_0 represents individual fixed effects; $CEE_{i,t}$ represents regional CEE;$DE_{i,t}$represents the digital economy;$ER_{i,t}$represents environmental regulation; $\sum_{j=1}^{n} X_{i,t}$ represents control variables, including industrial structure (IS), economic development level (GDP), resource endowment (RE), and openness (OP). γ_t, θ_i, and $\varepsilon_{i,t}$ represents regional effects, time effects, and random disturbance terms, respectively.

Variable selection and data sources

Explained variable

Regional CEE: This study employs the Super-Efficiency SBM model to measure regional CEE.

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Explanatory variables

Digital Economy (DE): Based on the understanding of the integration between the digital economy and the circular economy, and drawing upon domestic and international research, this study examines the application and penetration mechanisms of digital knowledge and technology within the circular economy in China. This analysis informs the development of an indicator system capable of precisely measuring the degree of integration between the digital economy and the circular economy, eliminating numerous indicators with high overlap and minimal impact. Drawing on the research of Zhao et al. (2020) and aligning with the essence of digital circular integration, we enhance regional comparability to construct the indicator system shown in *Table 2*.

Table 2. *Digital economy indicator system*

	Indicators	Unit
Digital economy	Internet users per 100 people	Per 100 people
	Percentage of computer services and software personnel	%
	Telecommunications service volume per capita	Ten thousand yuan
	Digital inclusive finance index	%
	Digital finance coverage breadth index	%
	Digital finance digitization level	%
	Percentage of enterprises engaged in e-commerce transactions	%
	E-commerce transaction volume	Ten thousand yuan
	Technology contract transaction value	Ten thousand yuan
	Digital technology related patent applications	Ten thousand items
	Internal research & development expenditure of industrial enterprises above designated size	Ten thousand yuan
	Telecommunications service volume	Ten thousand yuan
	Optical cable length	Km

Environmental Regulation (ER): Environmental regulation, also known as government control, involves administrative measures such as enacting relevant laws and regulations to prevent and control regional pollutant emissions. This aims to reduce the level of externalities, achieve environmental protection, and foster regional ecological innovation. Numerous indicators exist domestically and internationally for measuring the intensity of environmental regulation (Zhu et al., 2024; Zhao et al., 2025; Xiao et al., 2024; Jiang et al., 2024), primarily categorized as follows: 1) Based on the cost investment for pollutant reduction. Higher expenditure on pollutant reduction costs indicates greater regional environmental regulation intensity. 2) Using absolute pollutant emission levels as the metric, as outlined in the 13th Five-Year Plan for Ecological Conservation and Environmental Protection. Some scholars also employ pollutant removal rates for measurement, reflecting regional responses under varying environmental regulations. Higher values of this variable denote lower emissions of defined primary pollutants or "three wastes" (wastewater, waste gas, and solid waste). 3) From an administrative and legislative perspective, it is based on personnel or financial investments in environmental regulation, including the number of environmental protection system staff and the amount of investment in environmental pollution control. A higher value of this indicator indicates greater environmental regulation intensity. Considering the applicability and

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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effectiveness of the indicators, this paper adopts the third category of indicators mentioned above, using the amount of investment in environmental pollution control as the measurement indicator. Due to the dual characteristics of environmental regulation, this paper will further evaluate its nonlinear characteristics.

Control variables

Resource Endowment (RE): The resource endowment influences the circular economy development, and the two often exhibit a negative correlation. That is, the more abundant the natural resources, the higher the dependence on resources, and the lower the development level of the circular economy. Conversely, the higher the development level of the circular economy. Natural resources generally include water resources, mineral resources, forest resources, and climate resources. This study employs the ratio of persons engaged in extractive industries to total employed persons as the independent variable, reflecting mineral resource abundance. This is because, compared to water, forest, and climate resources, mineral resources exhibit a closer relationship with economic development. Selecting this indicator is more appropriate for measuring reduced energy inputs and the reuse levels of “three wastes” (wastewater, waste gas, and solid waste).

Economic Development (GDP): The CEE is basically in line with the level of economic development in each province, which is not a coincidence. The implementation of the circular economy requires a large amount of capital investment in technological research and development, equipment renewal, waste treatment and other aspects. The ability of a region to invest in industrial governance funds fundamentally depends on its economic development situation. Economically developed regions usually have stronger financial strength and richer social capital, which can provide sufficient financial support for circular economy projects. Under normal circumstances, we use the total GDP to represent the level of economic development in a region. Regions with higher GDP totals not only have more tax revenue, which can provide more funds for the government to use in environmental governance and the development of the circular economy, but also the enterprises in these regions are more capable of carrying out technological innovation and equipment upgrades, thereby improving resource utilization efficiency and reducing waste emissions. Therefore, the total GDP reflects to a certain extent the region’s ability to invest in and implement the circular economy.

Openness (OP): Opening up to the outside world is a double edged sword. On the one hand, it can attract new technologies and improve management levels. By integrating with the international market, domestic enterprises have the opportunity to access advanced production technologies and management concepts, thereby promoting their own technological innovation and management optimization. This technological spillover effect is of great significance for improving the production efficiency and product quality of enterprises, and further promoting industrial upgrading and economic restructuring. On the other hand, opening up to the outside world may also lead to the transfer of polluting industries. Some developed countries, in order to avoid strict environmental regulations in their own countries, may transfer high-pollution and high energy consuming industries to developing countries with relatively loose environmental regulations. Although this industrial transfer may bring certain economic growth in the short term, it will cause serious damage to the local environment in the long run and affect sustainable development. Therefore, the ultimate impact of opening up to the outside world is uncertain. In order to accurately measure the degree of opening up to the outside world and its impact on the economy and the environment, this paper uses the ratio of

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17011722

total imports and exports to GDP as a measure. This indicator can comprehensively reflect the extent of a country or region's participation in international trade and its level of economic openness. Through the analysis of this indicator, we can better understand the dual impact of opening up to the outside world on economic growth and environmental quality, and provide a scientific basis for formulating reasonable open policies.

Industrial Structure (IC): Among all the industries, the secondary industry has the most prominent impact on the environment. Therefore, this paper uses the proportion of industrial output value (total industrial output/GDP) to represent the industrial structure. At present, the secondary industry still has the tendency of high consumption and high emissions, which brings great pressure on the environment. Among them, the mining and manufacturing industries account for a relatively high proportion in the secondary industry. These two industries have relatively low resource utilization efficiency and large emissions of waste and pollutants. The high proportion of mining and manufacturing not only exacerbates the over exploitation and waste of resources, but also leads to serious environmental pollution problems, such as water pollution, air pollution and soil pollution. The existence of these problems makes the implementation of circular economy in these industries face many difficulties and challenges. To achieve the goal of circular economy, it is necessary to carry out in-depth structural adjustment and technological upgrading of these industries, improve resource utilization efficiency, reduce waste emissions, and promote the development of industries in a green and sustainable direction.

Results

Multicollinearity test

Prior to empirical testing, relevant tests were conducted to ensure data accuracy and applicability. The results are as follows: (1) VIF (variance inflation factor) tests were conducted on the explanatory and control variables in the model. *Table 3* shows that the maximum VIF value among all variables is 3.46, with the minimum being 1.66—both well below the critical threshold of 10. This indicates no multicollinearity issues exist.

Table 3. *Multicollinearity test results*

	ER	DE	RE	GDP	OP	IS	Mean
VIF	2.34	1.79	2.56	3.46	3.59	1.66	2.57
1/VIF	0.43	0.56	0.39	0.29	0.28	0.60	0.42

Testing for data stationarity

To avoid issues of spurious regression and false regression arising from nonstationary panel data, we first conduct stationarity tests on the panel data. Using the Levin, Lin, and Chu (LLC) test for both the dependent and independent variables, we obtain P = 0, strongly rejecting the null hypothesis of nonstationarity. This indicates that the data is stationary (see *Table 4*).

Generalized method of moments regression results

The validity of generalized method of moments estimation relies on the validity of instrumental variables. Two methods are typically used to identify whether the model

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DOI: http://dx.doi.org/10.15666/aeer/2401_17011722

specification is appropriate: first, the Hansen test—failure to reject the null hypothesis indicates the instrumental variables are correctly specified; second, testing whether the residuals from the difference in the regression system exhibit second order autocorrelation. The null hypothesis is the absence of autocorrelation. If the AR(1) and AR(2) tests reject and fail to reject the null hypothesis, respectively, the model specification is valid. The test results are shown in *Table 5*. The results indicate that the AR(1) test in this paper shows first order autocorrelation. Both the Hansen test and AR(2) test have P-values greater than 0.1, indicating no over identification and no second order serial correlation in the error term. The test results support the validity of the instrumental variables. The endogenous explanatory variable in this study is the lagged term of the dependent variable. To enhance the reliability of the regression results, tests were conducted on the model specification and the validity of the instrumental variables. The corresponding P-values for the Sargan tests are all greater than 0.5, indicating that the regression results do not suffer from over identification. This paper conducts separate regressions at the national level and for the eastern, central, and western regions. The division of China into these three economic zones is primarily based on geographical location differences and disparities in regional economic development levels. The eastern zone is located in coastal areas, possessing geographical advantages for opening up to the outside world; the central and western zones are defined by their inland geographical positions, situated in the central hinterland and remote western regions respectively. Concurrently, the eastern region exhibits significantly higher economic foundations, industrial structures, marketization levels, and development speeds compared to the central and western regions. China's eastern-western division is a policy-driven classification based on multiple factors, aimed at better formulating and implementing regional development policies to promote coordinated development across all regions. The regression results for different regions are presented in *Table 5*.

Table 4. *Data stationarity test CEE*

Variable	LLC		Stability
	Statistic	**P-value**	
CEE	-10.5643	0.0000	Steady
ER	-9.3345	0.0000	Steady
DE	-8.0953	0.0000	Steady
GDP	-11.2367	0.0000	Steady
OP	-8.0064	0.0000	Steady
IS	-3.6743	0.0002	Steady
RE	-3.9053	0.0001	Steady

In Model (1), the dependent variable represents forward looking production stage efficiency. Its first order lag term is significantly positive at the 10% level, indicating that improvements in the previous period's production stage efficiency promote enhancements in the current period's efficiency. This demonstrates the dynamic persistence of enhanced capabilities in efficient and clean production, while also validating the model specification of the dynamic panel regression.

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Table 5. *GMM regression results*

Variable	National	East	Central	West
DE	0.253***	0.356***	0.235***	0.103
ER	-0.197***	-0.125***	-0.235	-0.258
ER2	0.133***	0.158***	0.201	0.169
GDP	0.026***	0.133**	0.088**	0.014
IS	-0.144***	-0.113	-0.213***	-0.253***
RE	0.129	0.214	0.125**	0.233***
OP	0.036*	0.156***	-0.325	-0.135
AR(1)	0.003	0.012	0.023	0.046
AR(2)	0.156	0.231	0.158	0.211
Hansen	0.111	0.146	0.128	0.236
Sargan	0.632	0.552	0.598	0.612

(1) Impact of environmental regulations

At the national sample level, the regression coefficients for environmental regulations and their quadratic terms are both statistically significant at the 10% level. Moreover, the regression coefficient for the quadratic term is positive. indicating a U-shaped relationship between environmental regulations and CEE—initially inhibiting then promoting it. This can be interpreted as follows: Environmental regulations encompass both positive subsidies and negative penalty tools. During the implementation phase of positive subsidy tools, local governments invest in environmental infrastructure, crowding out potential production investments by enterprises and imposing indirect cost losses. During the initial phase of negative penalty tools, governments impose direct cost losses on enterprises through pollution fees and resource taxes, resulting in market-based regulations negatively impacting CEE. However, once regulatory intensity reaches a certain threshold—the Porter inflection point—the initial environmental investments resolve energy economic issues stemming from pollution. They reduce pollutant emissions during production while simultaneously accelerating corporate R&D into circular utilization technologies through pollution fees and resource taxes. Enterprises increasingly favored recycling production stage waste to enhance resource efficiency and reduce pollutant emissions, aiming to minimize pollution fees and resource taxes. The resulting “revenue compensation” gradually outweighed “cost losses,” generating an innovation compensation effect where environmental regulations positively impacted CEE.

When examining different regions, the first order and second order coefficients of the environmental regulation intensity variable in the central and western regions did not pass the significance test. This indicates that in these regions, the relationship between environmental regulation intensity and CEE is not significant. This may be because the environmental regulation policies in these regions have not been effectively implemented, or because enterprises’ responses to environmental regulation are not active enough. In contrast, in the eastern region, both the first order and second order coefficients of the environmental regulation intensity variable passed the 1% significance test, with the first order coefficient being negative and the second order coefficient being positive. This result shows that the development of the eastern region basically conforms to the theoretical assumption of this paper, that is, as the environmental regulation intensity

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increases from weak to strong, it will have a U-shaped impact on CEE, with an initial decrease followed by an increase. Specifically, when the environmental regulation intensity is low, enterprises may face certain economic pressures due to increased costs, leading to a decline in CEE. However, as the environmental regulation intensity further increases, enterprises gradually adapt and begin to adopt more advanced environmental protection technologies and management methods, thereby promoting the improvement of CEE. This U-shaped relationship reflects the important role of environmental regulation in promoting enterprise transformation and upgrading and improving resource utilization efficiency. The successful experience of the eastern region shows that reasonable environmental regulation policies can effectively promote the development of the circular economy and provide useful references for other regions. In the future, the implementation of environmental regulation policies should be further strengthened, while paying attention to the flexibility and adaptability of policies, in order to achieve sustainable development nationwide.

(2) Impact of the digital economy

Table 5 presents the regression results between the digital economy and CEE. The results indicate that the impact of the digital economy on low carbon CEE is positive at the 1% significance level. The impact coefficient of the digital economy is 0.253, which means that for every 1 percentage point increase in the level of the digital economy, the CEE index will rise by 0.253 percentage points. Specifically, the digital economy has promoted the improvement of CEE through various mechanisms. First of all, the digital economy has promoted the rapid circulation and sharing of information, enabling enterprises to more accurately grasp resource demand and market dynamics, thereby optimizing resource allocation and reducing resource waste. For example, through big data analysis, enterprises can predict market demand, arrange production plans reasonably, and avoid resource idleness and waste caused by overproduction. Secondly, the digital economy has driven technological innovation and industrial upgrading. The application of digital technology enables enterprises to adopt more efficient production technologies and management methods, improve production efficiency, reduce energy consumption and pollutant emissions. For example, intelligent manufacturing technology can achieve automation and intelligence in the production process, improve resource utilization efficiency, and reduce waste generation in the production process. In addition, the digital economy has also promoted the development of green supply chains. Through digital platforms, enterprises can better manage the flow of resources upstream and downstream of the supply chain, achieve recycling of resources and recycling of waste. For example, some enterprises have achieved precise procurement of raw materials and efficient recycling of waste by establishing digital supply chain management systems, improving the CEE of the entire supply chain. Overall, the digital economy has a significant role in improving CEE, which provides new ideas and directions for China to promote the development of the circular economy. In the future, the deep integration of the digital economy and the circular economy should be further strengthened. Through policy support and technological innovation, the widespread application of the digital economy in the field of the circular economy should be promoted to make greater contributions to the achievement of sustainable development goals.

Regionally, *Table 5* shows that the digital economy coefficient is significantly positive across eastern, central, and western regions, indicating that the digital economy can enhance CEE to a certain extent, thereby supporting the achievement of the “dual carbon”

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goals. Specifically, a proportional increase in the digital economy level in cities of both eastern and central regions promotes CEE. However, the enhancement effect is more pronounced in central regions. This finding aligns with the conclusions of She and Wu. (2022). This is because coastal regions and the six central provinces possess stronger economic foundations, with their digital economies ranking among the nation's largest. The digital economy generates spatial synergistic effects in promoting CEE—essentially creating positive externalities from economic agglomeration. These externalities transmit CEE through economic activities to neighboring regions, guiding technological adoption (Ge et al., 2022). The regression coefficient for the western region is positive but not significant, indicating that the development of the digital economy in western regions has not yet achieved a significant impact on local CEE. This may be because the influence of the digital economy on CEE has a certain scale threshold (Zhang et al., 2022), and only when the scale exceeds this threshold does a significant improvement effect occur.

(3) Effects of control variables

Economic development level exhibits a significant positive correlation with CEE, with a correlation coefficient of 0.1400. This indicates that higher economic levels correlate with greater CEE. This occurs because regions with advanced economies have largely moved beyond high input, low output, high pollution, low value added development models, while some backward production capacities have gradually shifted to less developed areas. The coefficient for the western region is significantly negative, while those for the eastern and central regions are significantly positive. This correlates with the western region's lower technological level and more primary industries, where economic growth has been achieved to some extent at the expense of resources and the environment.

The coefficient of industrial structure is significantly negative in all regions, which means that, overall, manufacturing plays an important role in promoting the circular economy but still has a long way to go in terms of energy conservation, emission reduction, and comprehensive utilization of resources. The greater the share of manufacturing, the greater the negative impact on the environment. Specifically, the manufacturing industry often consumes a large amount of energy and resources in the production process and generates a large amount of waste and pollutants. Without effective circular economy measures, it will put great pressure on the environment. However, although the eastern region is also negatively affected by manufacturing, this impact is not significant. This indicates that the eastern region has made rapid progress in the transformation and upgrading of traditional manufacturing. By adopting advanced production technologies, optimizing production processes, and improving resource utilization efficiency, it has effectively offset the negative impact of manufacturing on the environment. For example, many manufacturing enterprises in the eastern region actively introduce intelligent manufacturing technologies to achieve automation and precision in the production process, reducing energy waste and raw material consumption. At the same time, some enterprises have also established a sound waste recycling and reuse system, transforming waste generated in the production process into renewable resources and achieving circular use of resources. These measures not only improve the economic benefits of enterprises but also reduce environmental pollution and lay the foundation for the sustainable development of manufacturing in the eastern region. In contrast, the central and western regions may lag behind in the transformation and upgrading of manufacturing, so the negative impact of manufacturing on the environment

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is more obvious. This reminds us that we need to accelerate the transformation and upgrading of manufacturing in the central and western regions, improve its development level in the circular economy, and achieve sustainable development nationwide.

Foreign trade has a significant impact on the CEE of different regions. The eastern region, with its developed economy, advanced technology, and optimized industrial structure, can significantly improve CEE through foreign trade. These regions mainly export high value added high-tech products and high end manufacturing products, focusing on the efficient use of resources and recycling of waste during the production process. At the same time, advanced environmental protection technologies and circular economy concepts have also been widely applied. In contrast, the effect of foreign trade on improving CEE is not obvious in the central and western regions, especially in the central region. Although the central region exports a large quantity of products, they are mostly primary resource-based products with low added value and low resource utilization efficiency in the production process, which is often accompanied by serious environmental pollution and resource waste. For example, the export of mineral resources in some central provinces not only causes a lot of resource waste in the process of mining, processing, and transportation, but also causes serious damage to the local ecological environment, which greatly restricts the improvement of CEE.

The impact of national and eastern resource endowments on CEE is insignificant, likely because eastern China has historically maintained low resource dependency. Meanwhile, central China has benefited from technological advancements that enhanced mining efficiency, thereby raising the average energy efficiency of regions with favorable resource endowments. In the western region, each percentage point increase in resource endowment drives a 0.233 percentage point rise in CEE. This positive correlation between resource endowment and CEE in the west is counterintuitive. This unusual inverse relationship may stem from the rapid improvement in efficiency levels within petroleum, natural gas extraction, and other mining industries in recent years due to the widespread adoption of relevant technologies. Consequently, this has elevated the average energy efficiency of regions with better resource endowment.

Discussion

This study employs panel data from 30 Chinese provinces spanning 2009–2023. By constructing a dynamic panel model and applying the System GMM method, then examines the impact of the digital economy and environmental regulations on CEE at both national and regional levels. Key findings include:

First, environmental regulations exhibit a significant U-shaped relationship with circular economy efficiency, particularly pronounced at the national level and in eastern regions. This indicates the gradual emergence of an "innovation compensation effect," where enterprises enhance resource efficiency through green technological innovation and circular production models. This finding supports the "Porter Hypothesis" proposed by Porter and van der Linde (1995), which posits that well-designed environmental regulations can stimulate corporate innovation, thereby partially or fully offsetting environmental compliance costs and ultimately improving economic performance. The estimated coefficients for environmental regulations in central and western regions failed to pass significance tests. This may stem from local regulatory intensity not yet reaching the inflection point, low policy implementation efficiency, or industrial structures remaining highly resource-dependent.

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Second, the digital economy exerts a significant positive effect on circular economy efficiency. Except for the western region, all other regions show a significant positive correlation, indicating that digital technologies can effectively enhance circular economy efficiency by optimizing factor allocation, improving information transparency and coordination, and empowering green production processes. This conclusion resonates with the discussion by Han et al. (2022) on the mechanisms through which the digital economy promotes green development. Notably, while the digital economy coefficient for the western region is positive, it fails to pass the significance test. This suggests that the digital economy's promotion of the circular economy may involve a certain "scale threshold" or "development stage threshold." Its effects may only fully manifest once digital infrastructure construction and industrial integration reach a certain level. This phenomenon also aligns with Yu (2024) and Yang (2025) conclusion regarding regional heterogeneity in digital economic development.

Conclusions

This study conducting empirical research from both national and regional perspectives. Using CEE as the dependent variable, examining the impact of the digital economy and environmental regulations on CEE. The empirical findings yield the following conclusions:

At the national level, environmental regulations exhibit a U-shaped relationship with CEE, initially inhibiting and later promoting it. Once regulatory intensity reaches a certain threshold—the Porter inflection point—earlier environmental investments mitigate energy economic issues stemming from pollution. This reduces pollutant emissions during production and generates an innovation compensation effect, leading to a positive impact of environmental regulations on CEE. Regionally, neither the linear nor quadratic coefficients of environmental regulation intensity in central and western regions passed significance tests. In eastern regions, environmental regulations first reduced then enhanced CEE, confirming a U-shaped relationship between regulation intensity and performance.

The impact of the digital economy on low carbon CEE is positive at the 1% significance level. Across regions, the coefficients for the digital economy are significantly positive regardless of eastern, central, or western regions, indicating that the digital economy can enhance CEE to some extent, thereby supporting the achievement of the "dual carbon" goals. The regression coefficient for the western region is positive but not significant, suggesting that the development of the digital economy in the west has not yet produced a significant impact on local CEE. This may be because the influence of the digital economy on CEE has a certain scale threshold, and significant improvement effects only emerge when the scale exceeds this threshold.

Economic development level exhibits a significant positive correlation with CEE. The western region's coefficient is significantly negative, while the eastern and central regions show significant positive coefficients. This correlates with the western region's lower technological level and more primary industrial structure, where economic growth has been achieved at the expense of resources and the environment to some extent. The industrial structure coefficient is significantly negative across all regions, indicating that a higher share of manufacturing leads to greater negative environmental impacts. However, while the eastern region exhibits a negative impact, it is not statistically significant. This suggests that the eastern region has rapidly upgraded traditional

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manufacturing, offsetting the negative environmental effects. Foreign trade significantly enhances CEE in the eastern region but has a negligible effect in the central and western regions. Particularly in the central region, the large volume of exported products—mostly resource based primary goods—causes severe local environmental pollution and resource waste, hindering improvements in CEE. Nationally and in the eastern region, resource endowment has no significant impact on CEE. Conversely, the central and western regions benefit from technological advancements that enhance the efficiency of extractive industries, thereby raising the average energy efficiency in resource rich areas. This counterintuitive trend likely stems from the rapid improvement in efficiency levels of oil, natural gas extraction, and other extractive industries due to the widespread adoption of relevant technologies in recent years, which has elevated the average energy efficiency in resource rich regions.

Based on empirical analysis findings, this paper proposes the following recommendations to enhance regional CEE:

Appropriately strengthen environmental regulation intensity to leverage its purifying effect on economic development quality. Simultaneously, emphasize the coordinated and combined use of diverse environmental regulatory tools, focusing on both energy conservation and emission reduction to form synergistic efforts that drive circular economy performance improvement. When formulating and implementing environmental regulations, localities should establish standards within the capacity limits of enterprises while meeting national baseline environmental requirements. These regulations should undergo dynamic adjustments aligned with regional economic realities to avoid the pitfalls of either blindly tightening or relaxing regulatory intensity. This approach achieves a win-win outcome of improving the ecological environment and refining economic quality.

Advancing the “Digital China” initiative to create a new engine for green development. The digital economy plays a vital role in promoting economic growth, achieving structural transformation, and driving sustainable regional economic development. Localities should fully tap the potential of the digital economy, leveraging digital technologies to enhance production efficiency and resource utilization, reduce costs, decrease pollutant emissions, and propel the digital, intelligent, and green transformation of traditional industries. Governments play a vital role in digital economic development by increasing investment in digital infrastructure, narrowing the “digital divide,” and accelerating the digital economy’s capacity to advance green development and collaborative efforts.

Enhance regional green technological innovation capabilities to provide robust technical support for regional circular economic development. Green technological innovation minimizes ecological negative effects during scientific activities. Regions should fully recognize the critical role of green technological innovation in enhancing regional circular economy performance. Establish comprehensive green technology development and service centers to introduce and absorb advanced green technologies from abroad and other regions. Achieve breakthroughs and promote key technologies such as pollutant reduction, waste reuse, and clean production to further expand local green technology knowledge reserves and optimize the regional green technological innovation environment.

Governments should prioritize circular economy development as a key investment area, adjusting investment policies in a focused and selective manner. By increasing expenditures on scientific research and development while simultaneously boosting

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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pollution control investments, they can provide comprehensive financial support from source to end. For instance, direct investment in major projects that enhance CEE, or offering preferential loan terms and interest subsidies for such projects, can effectively leverage government investment to guide social investment toward circular economy initiatives. Concurrently, it is particularly important to encourage financial institutions to provide loan support for circular economy projects, establishing investment and financing models for circular economic development to rationally channel social and private capital flows.

Actively develop technologies to provide technical support for the circular economy. Implementing a circular economy requires an advanced scientific and technological system as its foundation. Key technologies for the circular economy include clean production techniques, pollution control technologies, industrial chain integration, and end of pipe pollution treatment methods. While eastern China has achieved some breakthroughs in circular economy technologies, there remains a significant gap compared to developed countries. The deficiencies in circular economy technologies across northeastern, central, and western regions are fundamental reasons for their relatively low efficiency in implementing such economies.

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DOI: http://dx.doi.org/10.15666/aeer/2401_17011722