Envisaging the carbon emissions efficiency of digitalization: The case of the Internet economy for China

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Abstract: With the successful convening of the 26th United Nations Climate Change Conference (COP26) and the constraints of carbon neutrality targets, China faces an increasingly severe task of energy conservation, reducing emissions, and improving carbon emission efficiency (CEE). The development of the Internet economy provides a perfect opportunity for China to realize the coordinated development of the economy and low-carbon society. Based on China's provincial panel data from 2006 to 2017, this paper explores the relationship between the Internet economy and CEE by using the instrumental variable-generalized method of moments (IV-GMM) method. It also investigates the internal mechanism and heterogeneity analysis. The main results show that (1) the Internet economy positively affects CEE in China; in other words, a 1% increase in Internet economy indicators will contribute to an increase of CEE indicators by 0.141%; (2) the Internet economy indirectly affects CEE by increasing human capital, clean technological innovation, and the non-coal energy mix; and (3) there is a significant asymmetric relationship between the Internet economy and CEE, with the negative influence of the Internet economy on CEE being more significant in southern China. This paper also proposes some policy implications to help China achieve low-carbon social development.

Keywords: Internet economy; Carbon emissions efficiency; Mediating effect; Heterogeneity analysis; China

JEL Classification: C33, L86, Q16, Q53, Q54

1. Introduction

Due mainly to excess greenhouse gas emissions, especially carbon dioxide (CO_2) emissions, climate change has gradually become a major problem facing all mankind (Gozgor, 2017; Rogge and Johnstone, 2017; Solomon et al., 2009; Zhao et al., 2021). To combat climate change, members of the United Nations and major organizations around the world convened at the 26th United Nations Climate Change Conference (COP26) in 2021 to jointly discuss the issue of climate change mitigation. Attending government members and other stakeholders reached consensus at the conference to keep the warming threshold at 1.5 degrees Celsius, reduce power generation from coal-fired power plants, and achieve net-zero emissions by the middle of this century (Basu et al., 2011; Maibach et al., 2021). As China is the world's largest developing country and has the largest carbon-emitting economy, its emission-reduction initiatives have attracted much attention (Gozgor and Can, 2017; Yang et al., 2020). As early as the Paris Agreement in 2015, the Chinese government proposed peaking CO_2 emissions around 2030, and reducing CO_2 intensity by another 18% by 2020 (Huang et al., 2021; Zhang et al., 2019); in the general debate of the 75th UN General Assembly, the Chinese government put forward higher requirements based on the 2030 carbon peaking goal; that is, carbon neutrality by 2060 (Hepburn et al., 2021). At the same time, China is facing the heavy task of economic growth. Since China has adhered to a coal-driven economic development model since the reform and opening up, in the context of mandatory constraints on carbon mitigation, coordinating economic development and emission-reduction actions have become major issues facing the country (Bhattacharya et al., 2015), so studies on carbon emission efficiency (CEE) are necessary.

The development of the digital economy represented by the Internet has become a significant driving force for China's economic development. According to data from the China Academy of Information and Communications Technology (CAICT), China's Internet penetration rate has risen to 70.4%, and the scale of Internet companies' receivables reached 3.4 trillion yuan in 2020. New economic models such as digital finance and online leasing have gradually become the main driving forces for economic development (CAICT, 2021). At the same time, the development of the Internet may also contribute to the high-quality development of China's energy and the mitigation of carbon emissions. The "Guiding Opinions on Energy Work in 2022" issued by the National Energy Administration (NEA) incorporates the construction of "Internet+" charging facilities into new energy industry planning and optimizes the layout of the renewable energy industry (NEA, 2022). Wang et al. (2022a) indicate that industrial digitalization will effectively promote the low-carbon industrial revolution and accelerate the process of greenhouse gas mitigation. However, some scholars have presented a contrasting point of view: they believe the Internet economy has spawned considerable use of equipment, resulting in increased power consumption, which is not conducive to environmental development (Park et al., 2018; Wang and Xu, 2021).

Therefore, there is still an uncertain relationship between the synergistic effect of the Internet on the economy and low-carbon development, which needs further exploration. In addition, we have noticed that Internet development promotes the high-quality and efficient development of enterprises, improves the quality of human capital, and accelerates clean technology innovation. Researchers have found that the use of the Internet has increased the employment rate of individuals, promoted labor participation, reduced the mismatch of human capital, and improved the product quality and efficiency of enterprises (Dettling, 2017; Kuhn and Mansour, 2014). Moreover, the integration of the Internet and the traditional energy industry has spawned new energy development models such as "Internet + smart energy" and "Internet + charging pile power generation," which have promoted technological upgrading and low-carbon development (Yu, 2022). And the Internet has accelerated the energy industry revolution and increased CEE. However, few scholars have explored the internal mechanism of the Internet economy affecting CEE. Finally, there are significant differences in the level of Internet development in China, so the development of differentiated industrial policies will benefit the development of China's low-carbon economy (Wang et al., 2022d).

Based on the above background, this paper will use panel data of 30 provinces in China from 2006 to 2017 to investigate the influence of the Internet economy on CEE by using the instrumental variable-generalized method of moments (IV-GMM) method, and further explore the internal mechanism and heterogeneity between them. Accordingly, this paper makes the following research contributions. First, the study explores whether the Internet economy is positively affecting CEE, which provides a policy reference for China's green development and fills a research gap. Second, we innovatively explore the internal mechanism of the Internet economy affecting CEE and provide references for government departments to formulate more detailed policies to help China achieve its carbon neutrality target. Third, we also explore the heterogeneity analysis between the Internet economy and CEE to provide a digital reference scheme for local governments to achieve emission reduction targets.

The literature review follows. In Section 3, we put forward the theoretical mechanism and hypotheses. In Section 4, we show the methodology and data. Sections 5, 6, and 7 discuss the estimation approaches and results. Section 8 concludes the results and sets out the policy implications.

2. Literature review

2.1. The measurements of CEE

CEE is a comprehensive indicator that not only describes the development of a green economy but also highlights the trend of energy conservation and emission reduction. Accordingly, many scholars have measured CEE. For example, Dong et al. (2022b) take 32 developed countries as a sample and measure their CEE levels. Their study shows that most developed countries are in a state of low efficiency. Zhou et al. (2010) measure the CEE of 18 of the world's largest carbon dioxide emitters; their results show that the overall level of CEE has increased by 24% due to technological progress.

As the world's largest carbon-emitting economy, China's CEE improvement is particularly important for energy conservation, emission reduction, and carbon neutrality. Therefore, many scholars have measured China's CEE level. For example, Sun and Huang (2020) analyze China's CEE using a parametric method (stochastic frontier model). Their results show that China's CEE has steadily improved. Dong et al. (2013), and Tan et al. (2020) also use the same parametric method to measure CEE levels in China, and although the sample selections are inconsistent, the authors reach similar conclusions. However, this approach suffers from the disadvantage that it requires a specific production function and technical configuration method to be pre-assumed before the efficiency calculation, which is usually unknown (Wang and Feng, 2021). Therefore, many scholars began to use non-parametric methods to measure the level of CEE in China. For example, Cheng et al. (2018) use an improved non-radial distance function to measure the total factor CEE index of industrial sectors in 30 provinces in China. The advantage of this method is that the technology gaps are considered. Their results show that CEE levels are highest in the eastern region, followed by the central region, and lowest in the western region. Yu and Zhang (2021) calculate China's CEE using a general nonconvex meta-frontier data envelopment analysis model. Their results show that CEE shows a rising trend over time. Other scholars have used nonparametric methods to measure China's CEE and obtained similar results (Wang et al., 2019a). In general, non-parametric measurement methods are more objective, and reliable, and have been recognized by more scholars. Therefore, we will use the most extensive data envelopment analysis (DEA) among non-parametric methods to explore CEE.

2.2. The nexus of the Internet economy and CEE

The Internet economy or technological challenges has effectively promoted the improvement of enterprises' performance, increased productivity, and further increased the green development of the economy (Cunningham and Thissen, 2012). Specifically, on the one hand, the Internet significantly affects the local economy. Liu and Chen (2021) point out that the role of the Internet in accelerating social and economic development is reflected in the provision of a new technological platform for the development of various industries, and the Internet itself has also become a form of development of the modern economy and society. Some scholars also highlight that the rapid development of Internet technology has made great contributions to China's remarkable economic achievements (Wan, 2021) and among other emerging economies (Tharriq et al., 2021). On the other hand, the Internet also has an impact on energy and the environment. For instance, Ren et al. (2021) point out that the Internet has broken geographic space boundaries, shortened the distance between regions, and integrated resources, thus having a negative impact on China's energy consumption. Yang et al. (2021) evaluate the impact of Internet development on smog pollution, and show that there is an inverted U-shaped curve nexus between Internet development and smog pollution in China.

However, as China is now constrained by emission-reduction targets, scholars are increasingly paying attention to the role of the Internet in reducing CO_2 emissions. For instance, Wang et al. (2022d) point out that the Internet economy has significantly reduced China's CO_2 emissions. Some scholars have also considered the synergy between CO_2 emissions and economic development. For instance, Wang et al. (2022c) evaluate the nexus between the Internet economy and green economic growth in China, and show that the Internet economy has contributed significantly to green economic growth by increasing environmental quality, industrial structure, and enterprise innovation. Lin and Zhou (2021) point out that the Internet economy can improve China's carbon emissions performance by promoting industrial structure upgrading and technology diffusion. Wu et al. (2021a) examine the influence of the Internet economy on China's green total factor energy efficiency (GTFEE), and show that Internet development improves GTFEE by decreasing the degree of source misallocation, regional innovation capabilities, and industrial structure upgrades.

2.3. Other determinants of CEE

In addition to Internet economy factors, economic growth, urbanization, industrial structural upgrading, and research and development (R&D) intensity will also affect CEE levels. For example, Sheng et al. (2020) confirm that there is a long-term coupling relationship between China's economic growth and CEE. Zhao et al. (2020b) also confirm that the negative relationship between urbanization and CEE is significant in China. Wang et al. (2019b) show that the rationalization and advancement of the industrial structure will help to improve the level of CEE. Dong et al. (2013) and Wu et al. (2021c) also believe industrial structure factors are important determinants of CEE.

Finally, Garrone and Grilli (2010) also confirm that R&D intensity is an important determinant of CEE.

2.4. Research gaps

According to the description of the above existing literature, we find that the method of measuring CEE has become mature. For China, many scholars have explored the development trend of CEE in various regions of the country, but there are still gaps in measuring the development level of CEE in each province. Second, few studies have focused on the role of the Internet economy on CEE; however, studying the nexus between the Internet economy and CEE can provide valuable references for China to achieve its carbon neutrality target. Third, it is of great significance to state that the internal mechanism between Internet development and CEE has not been clearly defined, and existing studies have ignored their heterogeneous effects.

3. Theoretical mechanism

3.1. The nexus of the Internet economy and CEE

The development of the Internet has brought about rapid economic growth, and initiated a clear trend of improvement in environmental performance (Lin and Zhou, 2021). CEE is the most obvious indicator of changes in the context of climate change, and the impact of the Internet economy on CEE is also very significant, as reflected in three main aspects. First, the Internet economy accelerates the speed of knowledge sharing, promotes economic growth (Litvinenko, 2020), and accelerates the iterative update of technology, thereby reducing energy consumption and pollution emissions, and improving CEE levels. Second, the Internet has given birth to emerging industries such as Internet finance, Internet energy, and the Internet industry, which not only enhances the vitality of the economy, but also improves industrial efficiency, promotes the development of low-carbon industries, and increases the level of CEE (Bai et al., 2021; Yang et al., 2022b). Third, the Internet has significantly promoted industrial upgrading, increased the proportion of high-tech industries, realized the digital penetration of traditional industries, accelerated industrial integration, and improved the level of CEE (Wang et al., 2022b; Yang and Wang, 2022). Therefore, we propose the following hypothesis:

Hypothesis 1. The Internet economy positively affects CEE.

3.2. The mediating effect between the Internet economy and CEE

Since the popularization of the information economy and the digital economy, Internet applications have been changing the employment models, industrial organization, and corporate performance of enterprises. Therefore, the development of the Internet has promoted a significant change of human capital. The reasons are as follows. From the perspective of enterprise employment, the application of the Internet has changed the employment mode of enterprises. In particular, the application of Internet technology in production management has promoted the generation of new knowledge and technologies in enterprises, which requires enterprises to improve the technical aptitude and knowledge of workers to adapt to new changes (Passerini and Granger, 2000; Santoro et al., 2018). From the perspective of the employees themselves, the Internet has increased ways for them to acquire skills and made it more convenient to acquire knowledge, which is conducive to improving the knowledge and skill levels of employees (Isaac et al., 2017). From a social point of view, the Internet has added new jobs, provided more high-level talent acquisition channels for enterprises, and provided a fair interaction platform between supply and demand sides, which makes the matching between enterprises and employees more suitable and promotes the level of human capital. According to evidence from the endogenous growth model, the accumulation of human capital will contribute to production, creating economic levels (Romer, 1990). And a favorable level of education and high-tech personnel create a stronger awareness of energy conservation (Edziah et al., 2021). Therefore, by combining the above two aspects, it is clear human capital is conducive to promoting the improvement of CEE.

The continuous integration of the Internet and various fields of economy and society have provided sufficient impetus for the realization of green development (Li et al., 2022). In this process, clean technological innovation is considered to be an effective tool to change the balance between environmental degradation and economic growth (Ali et al., 2021; Rogge and Schleich, 2018). On the one hand, the Internet is embedded in the production activities of energy companies, and by promoting long-term trust in clean energy products, the level of clean energy technology and new knowledge will improve (Yu, 2022). On the other hand, the Internet has an obvious role in knowledge spillover. The dissemination and diffusion of information within the energy industry accelerates information sharing and exchanges and promotes the level of clean technological innovation (Bloom et al., 2013). Clean technological innovation can improve production processes and promote solutions for replacing fossil energy with renewable energy, thereby increasing energy efficiency and CEE (Chen et al., 2021; Gozgor and Paramati, 2022).

The Internet significantly affects the energy mix. On the one hand, the application of the Internet to energy has promoted the development of intelligent energy, changed the ways of producing energy and consuming it, and upgraded the industrial structure (Ren et al., 2021). On the other hand, the Internet can build a renewable energy development platform, plan energy production and consumption patterns, optimize resource allocation, and promote energy upgrades (Zuo et al., 2018). The upgrade of the energy structure promotes the development of renewable energy, reduces CO_2 emissions, and improves the vitality of economic development, thus promoting the improvement of CEE.

Hypothesis 3. The Internet economy indirectly improves CEE by increasing the level of human capital.

Hypothesis 4. The Internet economy indirectly improves CEE by increasing the level of clean technological innovation.

Hypothesis 5. The Internet economy indirectly improves CEE by changing the energy mix.

4. Estimation model and data

4.1. Model setting

To investigate the impact of the Internet economy on CEE, this paper constructs a theoretical model based on previous theoretical models (Dong et al., 2022a; Sun and Huang, 2020; Wang et al., 2022d) and Hypothesis 1:

$$lnCEE_{it} = \alpha_0 + \alpha_1 lnINT_{it} + \sum_{k=2}^{5} \alpha_k lnX_{it} + e_{it} \quad (1)$$

where i represents individuals, t represents years, CEE_{it} indicates carbon emissions efficiency; INT_{it} represents the Internet economy; X_{it} denotes the control variables, which include economic growth ($PGDP$), industrial structural upgrading (IND), R&D intensity (RD), and urbanization (URB). $\alpha_1, \cdots, \alpha_5$ denote the estimated coefficient, α_0 denotes the constant terms, and e_{it} denotes the random disturbance term. In addition, according to Hypothesis 1, we assume $\alpha_1 > 0$.

Further, to explore the internal mechanism of the role of the Internet economy on CEE (Hypotheses 2-4), this paper refers to the method of Baron and Kenny (1986), and constructs the following theoretical model:

$$lnM_{it} = \delta_0 + \delta_1 lnINT_{it} + \sum_{k=2}^{5} \delta_k lnX_{it} + e_{it} \quad (2)$$

$$lnCEE_{it} = \eta_0 + \eta_1 lnINT_{it} + \eta_2 lnM_{it} + \sum_{k=3}^{6} \eta_k lnX_{it} + e_{it} \quad (3)$$

where $\delta_1, \cdots, \delta_5$ and $\eta_1, \cdots, \eta_6$ are the estimated coefficients, δ_0 and η_0 denote the constant terms, and M_{it} denotes the mediating variables, including human capital (HUM_{it}), clean technological innovation ($RETI_{it}$), and energy mix (EM_{it}). If both the estimated coefficients of φ_1 and η_2 are significant, the mediating variables exercise mediating effects between the Internet economy and CEE. In other words, hypotheses 2-4 are verified.

4.2. Variable definitions and data

4.2.1. Dependent variable

To determine the relative efficiency level of a group of decision-making units (DMUs), the general method is to use the non-parametric technical efficiency analysis method, of which the most widely used is the DEA method (Farrell, 1957). The principle number of the DEA model uses mathematical programming to compare the degree of deviation of a group of DMUs from the production frontier. As a kind of DEA model, the SBM model with undesirable output is effective for calculating eco-efficiency (Du et al., 2021; Zhao et al., 2020a).

In the production system, n DMUs are supported, and each DMU consists of three factors: input, desirable output, and undesirable output. By using m input factors, each DMU has s_1 desirable outputs and s_2 undesirable outputs. And input factor $x \epsilon R^m$; desired output $y^d \epsilon R^{s_1}$; and undesired output $y^u \epsilon R^{s_2}$. Therefore, the factors of all DMUs can be organized in matrix form $X = [x_1, x_2, \cdots, x_n] \in R^{m \times n}$, $Y^d = [y_1^d, y_2^d, \cdots, y_n^d] \in R^{s_1 \times n}$, $Y^u = [y_1^u, y_2^u, \cdots, y_n^u] \in R^{s_2 \times n}$. We also assume $X > 0$, $Y^d > 0$, and $Y^u > 0$, and the production possibility set (PPS) is described as follows:

$$P(x) = \{(y^d, y^u) | x \; produce (y^d, y^u), x \geq X\lambda, y^d \leq Y^d\lambda, y^u \geq Y^u\lambda, \lambda \geq 0\} \quad (4)$$

where λ is the non-negative intensity vector. Tone (2004) invested Tone's SBM model. However, we indicate that the SBM model has obvious flaws, such as the inability to rank DMUs with an efficiency of 1. Based on this, Li et al. (2013) and Lee and Lee (2022) improve the above model to obtain the super-SBM model with undesirable output, which is set as:

$$\rho_s = min \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}}{x_{i0}}}{\frac{1}{s_1+s_2}\left(\sum_{p=1}^{s_1}\frac{\bar{y}^d}{y_{p0}^d}+\sum_{q=1}^{s_1}\frac{\bar{y}^u}{y_{q0}^u}\right)}$$
$$s.t.\begin{cases} \bar{x} \geq \sum_{k=1,\neq 0}^{m} x_{jk}\lambda_k \\ \bar{y}^d \leq \sum_{k=1,\neq 0}^{s_1} y_{pk}^d\lambda_k \\ \bar{y}^u \geq \sum_{k=1,\neq 0}^{s_2} y_{qk}^u\lambda_k \\ \bar{x} \geq x_{jk}, \bar{y}^d \leq y_{pk}^d, \bar{y}^u \geq y_{qk}^u, \lambda_k \geq 0 \end{cases} \tag{5}$$

where, ρ_s is the super efficiency value, which can be larger than 1; $\bar{x}$ is the mean vector of inputs, $\bar{y}^d$ is the mean vector of desirable output, and $\bar{y}^u$ is the mean vector of undesirable output. The super-SBM model effectively solves the input and output slackness problems caused by radial and angular selection (Song et al., 2012), and also effectively solves the excess input and output gaps in the measurement. Therefore, we use this method to calculate CEE (Teng et al., 2021).

According to the setting of previous research, this paper considers three input variables, one desirable output, and one undesirable output when calculating the CEE, as shown in Table 1. Labor input is proxied by the number of workers in each province. Capital input is measured by investment in fixed assets. Energy input is proxied by total energy use (Lee and Lee, 2022). Among them, the capital stock is measured by the perpetual inventory method, with 2002 as the base year. All data have been converted into 2006 constant prices.

Insert Table 1

4.2.2. Independent variable

As the proxy variable of the Internet economy, the Internet development index comes from Ren et al. (2021) and Wang et al. (2022d). This index comprises four aspects. The detailed indicators are shown in Table 2.

Insert Table 2

4.2.3. Mediating variables

Human capital, as measured by the aggregate number of years of education per capita (Wang et al., 2021c), can be calculated by the following equation:

$$HUM_{it} = 6 * Labor_{primary,it} + 9 * Labor_{junior,it} + 12 * Labor_{senior,it} + 16 * Labor_{college,it} \quad (6)$$

where $Labor_{primary}$, $Labor_{junior}$, $Labor_{senior}$, and $Labor_{college}$ denote the proportion of the labor force with only a primary school education, a senior middle school education, a senior high school education, and a college education, respectively.

Clean technology innovation is measured by the renewable energy technology innovation index (Cheng and Yao, 2021), and the calculation equation is:

$$RETI_{it} = REPS_{it} + (1 - \phi)RETI_{it-1} \quad (7)$$

where $REPS$ represents the renewable energy patents stock, and ϕ is the depreciation rate. Referring to Bottazzi and Peri (2007), ϕ can be set as 10%. The patent data in China comes from the Patent Search System of the State Intellectual Property Office of China [1]. The search method uses the patent classification number,

[1] http://www.pss-system.gov.cn/.

which comes from the International Patent Classification (IPC) Code. Since the statistics of Chinese patents began in 1985, our data are also accumulated from 1985. The specific classification codes of each renewable energy technology are shown in Table A1.

Finally, energy mix, as a mediating variable, is measured by the proportion of coal energy consumption.

4.2.4. Control variables

To avoid omitted variable bias, this paper selects four control variables that may affect CEE. (1) Economic growth ($PGDP$), as measured by GDP per capita; (2) Industrial structural upgrading (IND), as calculated by the ratio of value-added of tertiary industry to secondary industry; (3) R&D intensity (RD), as measured by the share of R&D expenditure to GDP; and (4) Urbanization (URB), as measured by the share of the urban population.

4.3. Data sources and statistical description

In this research, we use a panel dataset of 30 provinces in China between 2006 and 2017, excluding Tibet, Hong Kong, Macao, and Taiwan. The data sources of other indicators for calculating CEE are represented in Table 1, and the data sources of indicators for calculating the Internet economy are shown in Table 2. Moreover, the data on the average years of education are derived from the China Labor Statistical Yearbook (NBS, 2022b). In addition, the data on total energy consumption and coal energy consumption are from the China Energy Statistical Yearbook (NBS, 2022a).

Other data are from the China Statistical Yearbook (NBS, 2022c). Table 3 presents descriptive statistics for the above variables.

Insert Table 3

5. Estimation approaches and empirical results

5.1. Characteristics of CEE and the Internet development indexes

Fig. 1 shows the spatial distribution of the CEE indicators and the Internet economy indicators of China. The CEE indicators of most provinces show an upward trend, which has also been confirmed by Sun and Huang (2020). This is because China has played a significant role in reducing CO_2 emissions in recent years. As China plays an increasingly important role in mitigating climate change in the international community in both the 13th Five-Year Plan and 14th Five-Year Plan, China regards carbon-emission reduction and energy-intensity reduction as important implementation strategies. The Internet economy indicators of most provinces have represented a weak upward trend due to China's policy inclination towards the digital economy and Internet economy in recent years, including "Broadband China," "Internet Finance," and "Internet +Smart Energy" (NDRC, 2016; The State Council, 2013, 2015). Provinces with more developed economies, such as Beijing, Shanghai, and Guangdong have relatively higher Internet economy indicators, while inland provinces have relatively lower Internet economy indicators. A potential explanation is that provinces with more developed economies usually have a relatively complete level of Internet development, and many Internet companies are concentrated, which promotes the development of the local Internet economy.

Insert Fig. 1

5.2. Benchmark results

To solve the potential endogeneity problem, this research adopts the IV-GMM method to evaluate the influence of the Internet economy on CEE (Adams et al., 2020; Muhammad et al., 2022). In terms of the test results of the IV-GMM technique (see Table 4), the p-values of the Kleibergen-Paap rk Lagrange Multiplier statistic are smaller than 0.1, which indicates that the instruments are not under-identified (Kleibergen and Paap, 2006). The Kleibergen-Paap rk Wald F-statistics are larger than 10, indicating that the instruments are not weak. And the p-values of the Hansen J statistics are larger than 0.1, which indicates that all instrument variables are not over-identified (Lee and Moumbark, 2022). The above tests confirm that the IV-GMM results are robust.

As represented in column (1) of Table 4, the coefficient of $lnINT$ is positive at the 1% significant level, which is estimated by Eq. (1). This result indicates that the Internet economy positively affects CEE. In other words, a 1% rise in Internet economy indicators will contribute to an increase of CEE indicators by 0.141%. First, the development of the Internet can significantly increase the management efficiency of enterprises, improve the speed of information processing and exchange, and then improve energy efficiency and CEE (Lin and Zhou, 2021). Second, the development of the Internet has promoted the exchange of information between industries and accelerated the speed of technological development, thereby decreasing energy consumption and CO_2 emissions, and achieving the improvement of CEE (Wang et al., 2022d). In addition, we consider that China has used big data, digital economy, and other related technologies to accelerate the development of clean energy in recent years to achieve the target of carbon neutrality, which has also promoted the improvement of China's CEE (Wang et al., 2022a; Wang et al., 2021b). Hypothesis 1 has been verified.

Column (1) of Table 4 also represents the determinants of CCE. First, the coefficient of $lnPGDP$ is 0.420 at the 1% significant level, which indicates that economic growth contributes significantly to an increase in CCE. A potential explanation is that China has been actively concerned about the negative influence of economic growth on the environment in recent years. It has issued relevant policies to control pollution and greenhouse gas emissions. The policies include the 13th and 14th Five-Year plans, which clearly underscore the importance of reducing emissions (Stern and Xie, 2022). Second, the coefficient of $lnIND,$ which indicates industrial structural upgrading in China, will significantly increase CEE and is significantly positive. This is because a single industrial structure will lead to resource dependence, and industrial upgrading has effectively promoted the use of low-carbon energy, improved technological innovation capabilities, and increased CEE (Wang et al., 2019b). Third, the coefficient of $lnRD$ is positive at the 1% significance level. The increase in R&D

intensity leads to an improvement of the local technical level, which improves the productivity and R&D quality of enterprises (Fisher-Vanden and Sue Wing, 2008), and is conducive to reducing energy consumption and improving the economic level. Jiao et al. (2018) also confirm the negative effect between R&D intensity and carbon emissions in China. Therefore, we believe that R&D intensity effectively improves CEE in China.

Columns (2) – (5) of Table 4 represent the estimated results of the four sub-indicators of the Internet economy on CEE, respectively. The estimated results show that the coefficients of Internet penetration ($lnINT1$), Internet infrastructure ($lnINT2$), and Internet application ($lnINT4$) are significantly positive. First, the Internet penetration rate indicates the popularity of the Internet. A higher Internet penetration rate can reduce information asymmetry and improve transmission efficiency, which is conducive to the improvement of CEE. It is worth noting that the coefficient of Internet penetration is higher than the coefficient of the other two sub-indicators, which indicates that effectively increasing the Internet penetration rate will be the best way to improve CEE. Internet infrastructure reflects the basic capabilities of local Internet, which is also a significant foundation for the future development of the Internet economy. Therefore, a better Internet infrastructure level will promote the faster realization of the information development of enterprises, promote the improvement of the digitalization level of the industrial chain, and realize the positive spillover effect of information resources. Finally, Internet applications can also effectively promote the level of CEE. This is because the telecommunications industry and the postal industry can enable people to shop, communicate, and work without leaving home (Loo and Wang, 2018), reducing energy consumption and stimulating economic development.

Insert Table 4

5.3. Robustness checks

In Table 5, we perform three robustness tests. Column (1) shows the regression results using Lewbel's instrumental variable model (Lewbel, 2012; Shahbaz et al., 2022). The estimated results of all the independent variables are significantly positive except for $lnURB$, which is in line with the estimated results of benchmark regression (column (1) of Table 4). And it further confirms that the Internet economy positively affects CEE.

In 2013, the State Council promulgated the "Broadband China" strategy, which aims to improve the construction of China's information infrastructure, narrow the gap with developed countries, and achieve rapid Internet penetration (Fang et al., 2022; The State Council, 2013; Yang et al., 2022a). Therefore, we divide the sample into two groups, 2006-2013 and 2014-2017, respectively, estimate their results, and list them in columns (2) and (3). The coefficients of $lnINT$ are significantly positive, which further confirms the robustness of benchmark regression.

Third, we substitute the value-added proportion of tertiary industry as a proxy variable for industrial structural upgrading. The estimated results (column (4) of Table

5) show that the coefficients' direction and the significance of all the independent variables are in line with the benchmark regression.

Finally, we apply the number of websites as the instrumental variable for the Internet economy, and estimate the regression results in column (5) of Table 5. The coefficient of $lnINT$ is also positive at the 1% significance level, which shows that the Internet economy positively affects CEE. The above robustness checks all confirm that the results of the benchmark regression are robust.

Insert Table 5

6. Mediating effect on the nexus of the Internet economy and CEE

According to Hypotheses 2 – 4, we believe there are three potential paths for the Internet economy to affect CEE, namely human capital, clean technological innovation, and adjusting the energy mix.

6.1. Mediating effect of human capital

The results of benchmark regression in column (1) of Table 6 indicate that the Internet economy positively affects CEE in China. In column (2) of Table 6, the coefficient of $lnINT$ is positive at the 1% significance level, which indicates the Internet economy has a positive influence on human capital. Column (3) of Table 6 show that the coefficient of $lnHUM$ is positive at the 1% significance level, and the coefficient of $lnINT$ is also significantly positive. The above results represent that the

Internet economy indirectly affects CEE by increasing the level of human capital. Many scholars have corroborated this result. For example, Raab et al. (2001) believe the development of the Internet will enable more people to obtain online learning opportunities and make education more equal and accessible. Therefore, the Internet has proved to be conducive to the advancement of human capital. Ren et al. (2021) and Wu et al. (2021b) also confirm that the Internet economy positively affects human capital. Enhancing human capital have been proven as influences of energy efficiency in developing countries (Edziah et al., 2021; Mubarik and Naghavi, 2022), and the positive externalities of human capital promote green development and increase industrial efficiency, thus benefiting CEE. The above results confirm the correctness of Hypothesis 2; that is, the Internet economy indirectly promotes CEE by enhancing human capital.

6.2. Mediating effect of clean technological innovation

Columns (4) - (5) of Table 6 check the mediating impact of clean technological innovation in the course of the Internet economy affecting CEE by estimating Eqs. (2) and (3). Column (4) shows that the coefficient of $lnINT$ is significant (0.352), indicating that a 1% rise in Internet economy indicators will cause a 0.352% increase in clean technological innovation. From the estimated results of column (5), the coefficient of clean technological innovation is significantly positive, and the coefficient of the Internet economy is also significantly positive. The above results also show that the Internet economy indirectly affects CEE by improving clean technological innovation. The development of the Internet has brought advantages to clean energy technology, lowered the threshold for the use of clean energy technology, opened up restrictions between traditional industries and clean industries, and promoted clean technology innovation (Yu, 2022). Relying on the strong economic strength of Internet companies, China has accelerated the construction of "smart energy" and promoted the rapid popularization of renewable energy power generation. Moreover, clean technological innovation is considered an effective means of balancing environmental pollution and economic growth. For example, Ali et al. (2021) confirm that clean technological innovation has a significant negative impact on greenhouse gas emissions and a significant positive influence on economic growth in G-7 countries. Therefore, Hypothesis 2 is confirmed.

6.3. Mediating effect of the energy mix

Columns (6) - (7) of Table 6 check the mediating role of the energy mix in the course of the Internet economy affecting CEE by estimating Eqs. (2) and (3). The coefficient of $lnINT$ is negative at the 1% significance level, which indicates that the Internet economy negatively affects the coal energy mix. Hou et al. (2018) point out that the application of the Internet in the energy field has promoted the rapid development of China's natural gas industry. He et al. (2020) also point out the promotion role of the Internet economy on renewable energy. Therefore, the application of the Internet in the energy industry has accelerated the energy transition process, reduced the use of high-carbon energy through a highly integrated and information-based system, and promoted the optimization of the energy structure. As shown in column (7) of Table 6, the coefficient of $lnEM$ is significantly negative, and the coefficient of $lnINT$ is significantly positive, which indicates that the Internet economy positively affects CEE by optimizing the energy mix. The increase in the proportion of clean energy will help achieve carbon emissions-reduction goals and improve the efficiency of green development (Wang et al., 2021a). Therefore, Hypothesis 3 is confirmed. To more clearly show the mediating role of the Internet economy affecting CEE, this paper draws Fig. 2.

Insert Table 6

Insert Fig. 2

7. Heterogeneity analysis

7.1. Asymmetric check

Table 7 represents the estimated coefficients of all the independent variables by using quantile regressions. Further, to more clearly see the quantile effect of each variable on CEE, we also draw Fig. 3. The results indicate that the positive impact of the Internet economy on CEE is further confirmed. Except for the 25th quantile, the results on other quantiles confirm that the Internet economy significantly affects CEE. This means that in areas with higher or lower CEE indicators, the Internet economy has significant effects on CEE. Section 5.1 shows that the provinces with higher CEE are concentrated in the southeastern coastal areas of China, where there are abundant Internet resources. Their Internet development has a high ability to coordinate and optimize resources, promote innovation of local enterprises, and achieve optimal allocation of resources. In addition, provinces with higher CEE also indicate that they prioritize the coordinated governance of economic development and carbon emission reduction, and have rich development experience (Tao, 2022). The Internet economy enables them to achieve a higher level of carbon emission-reduction governance. In provinces with lower CEE levels, there are problems such as wasted resources, excessive consumption of fossil energy, and slow economic development. The Internet economy can promote the rapid upgrading of the local industrial structure and the development of clean energy technologies, thus enabling faster energy optimization and carbon mitigation.

Insert Table 7

Insert Fig. 3

7.2. Heterogeneity checks about regional location

Further, we divide Chinese provinces into southern and northern provinces according to the Qinling-Huaihe line (the specific list of provinces is shown in Table A2) (Yang and Wang, 2022), and estimated the sub-samples of the two regions respectively. The results are presented in Table 8. The coefficient of the Internet economy is significantly positive in the sample regression of southern China, but the coefficient of the Internet economy is not significant in the sample regression of northern China. This shows that the Internet economy in the southern provinces of China can significantly promote the improvement of CEE, but the role of Internet development in the northern provinces in the improvement of CEE is not obvious, and there may be a reduction effect. A potential reason is that since China's reform and opening up, the economic center has moved south, and a large number of emerging technology industries are developing rapidly in the southern provinces (e.g., Huawei, Tencent, Alibaba, etc.). This has promoted them to drive the upgrading of the surrounding industries, improve the efficiency of the industrial chain, promote the optimal allocation of resources, and enhance local green development. Facts have proved that the southern provinces have achieved remarkable results in terms of economic development and environmental governance (Li et al., 2020), and carbon-emission governance has achieved initial results. China's Southern Power Grid expects to achieve more than 60% of non-fossil energy power generation by 2025 [2]. However, the northern provinces of China have gathered a considerable number of heavy industries, the economic transformation is facing difficulties, and the problem of environmental pollution is more serious. The development of the Internet economy may be out of touch with the traditional industrial sector, and it is difficult to achieve industrial convergence (Yang and Wang, 2022). Thus, the Internet economy in the northern provinces does not significantly promote CEE.

[2] See http://eng.csg.cn/Press_release/News_2021/202112/t20211213_324215.html.

Insert Table 8

8. Conclusions and policy implications

8.1. Conclusions

Considering the potential relationship between the Internet economy and CEE, this paper uses the IV-GMM technique to investigate the role of the Internet economy on CEE in 30 provinces in China from 2006 to 2017, and on this basis, examines the potential internal mechanism and heterogeneity of the Internet economy and CEE. Our study makes the following conclusions: (1) Based on the panel data of 30 provinces in China, the Internet economy positively affects CEE, and Internet penetration, Internet infrastructure, and Internet application play important roles in increasing CEE in China; (2) human capital, clean technological innovation, and energy mix play increasingly important mediating roles of the Internet economy in China; (3) in terms of the results of the asymmetric check, the positive influence of the Internet economy on CEE is driven by all quantiles except for the 25th quantile; and (4) the results of regional heterogeneity show that a significant positive effect between Internet economy and CEE exists only in the Southern China sample estimates.

8.2. Policy implications

We also put forward some policy implications. On the one hand, the Chinese government should promote the rapid development of the Internet economy, speed up research and development services of information technology, formulate relevant policies, and build an Internet development center to promote the green penetration of the information industry. On the other hand, the government should accelerate the popularity of the Internet in households and enterprises, and lay out Internet infrastructure across the country. The government should also focus on improving the information industry in future policies, building the Internet of things and big data services, and expanding the greening influence of the information industry.

Second, the Chinese government should focus on the Internet in promoting human capital, such as popularizing Internet courses, using Internet resources in enterprises to provide technical training to employees, and improving the production efficiency of enterprises. The government should guide enterprises to apply more emerging technologies to the development of clean energy, accelerate technology research and development, and provide policy support, professional guidance, and financial assistance to help enterprises improve performance and achieve carbon neutrality targets more quickly. The Chinese government should follow the actions agreed at COP26 to reduce power generation from coal-fired power plants and commit to replacing electricity with clean energy. The government should also help energy and Internet companies achieve convergence development, and promote the transformation and assistance of the Internet to the energy industry. For instance, the traditional energy industry has actively introduced digital tools and Internet services to guide the digital transformation of enterprises. Government-enterprise integration services should be improved, and realize the dual development of low-carbon government and enterprise.

Third, differentiated Internet performance improvement policies should also be taken seriously. Governments in areas with lower CEE should actively introduce Internet companies to stimulate local economic development while promoting the intelligence and informatization of the industrial chain to achieve green and low-carbon development. Provinces with higher CEE should expand the convergence of the information industry and traditional industries, establish green information industry parks, and promote the further improvement of local greening levels. In addition, the northern provinces of China should accelerate economic transformation, enhance the informatization penetration of heavy industry, and promote the development of the clean energy industry to realize the improvement of CEE.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Disclosure statement

No potential conflict of interest was reported by the authors.

Appendix

Table A1. Patent classification codes of renewable energy technologies.

Technologies	IPC Codes
Hydro energy	E02B9/00 OR E02B9/01 OR E02B9/02 OR E02B9/03 OR E02B9/04 OR E02B9/05 OR E02B9/06 OR E02B9/08 OR F03B OR F03C OR B63H19/02 OR B63H19/04
Wind energy	F03D OR H02K7/18 OR B63B35/00 OR E04H12/00 OR B60K16/00 OR B60L8/00 OR B63H13/00
Solar energy	F24S OR H02S OR H01L27/142 OR H01L31/00 OR H01L31/01 OR H01L31/02 OR H01L31/03 OR H01L31/04 OR H01L31/05 OR H01L31/06 OR H01L31/07 OR H01L31/08 OR H01L31/09 OR H01L31/10 OR H01L31/11 OR H01L31/12 OR H01L31/13 OR H01L31/14 OR H01L31/15 OR H01L31/16 OR H01L31/17 OR H01L31/18 OR H01L31/19 OR H01L31/20 OR H01L31/21 OR H01L31/22 OR H01L31/23 OR H01L31/24 OR H01L31/25 OR H01L31/26 OR H01L31/27 OR H01L31/28 OR H01L31/29 OR H01L31/30 OR H01L31/31 OR H01L31/32 OR H01L31/33 OR H01L31/34 OR H01L31/35 OR H01L31/36 OR H01L31/37 OR H01L31/38 OR H01L31/39 OR H01L31/40 OR H01L31/41 OR H01L31/42 OR H01L31/43 OR H01L31/44 OR H01L31/45 OR H01L31/46 OR H01L31/47 OR H01L31/48 OR H01L31/49 OR H01L31/50 OR H01L31/51 OR H01L31/52 OR H01L31/53 OR H01L31/54 OR H01L31/55 OR H01L31/56 OR H01L31/57 OR H01L31/58 OR H01L31/59 OR H01L31/60 OR H01L31/61 OR H01L31/62 OR H01L31/63 OR H01L31/64 OR H01L31/65 OR H01L31/66 OR H01L31/67 OR H01L31/68 OR H01L31/69 OR H01L31/70 OR H01L31/71 OR H01L31/72 OR H01L31/73 OR H01L31/74 OR H01L31/75 OR H01L31/76 OR H01L31/77 OR H01L31/78 OR H01G9/20 OR H01L27/30 OR H01L51/42 OR H01L51/43 OR H01L51/44 OR H01L51/45 OR H01L51/46 OR H01L51/47 OR H01L51/48 OR H01L25/00 OR H01L25/03 OR H01L25/16 OR H01L25/18 OR H01L31/042 OR C01B33/02 OR C23C14/14 OR C23C16/24 OR C30B29/06 OR G05F1/67 OR F21L4/00 OR F21S9/03 OR H02J7/35 OR H01M14/00 OR F24D17/00 OR F24D3/00 OR F24D5/00 OR F24D11/00 OR F24D19/00 OR F03D1/04 OR F03D9/00 OR F03D13/20 OR C02F1/14 OR F02C1/05 OR H01L31/0525 OR B60K16/00 OR B60L8/00 OR F03G6/00 OR F03G6/01 OR F03G6/02 OR F03G6/03 OR F03G6/04 OR F03G6/05 OR F03G6/06 OR E04D13/00 OR E04D13/18 OR F22B1/00 OR F24V30/00 OR F25B27/00 OR F26B3/00 OR F26B3/28 OR G02B7/183
Biomass energy (Bio-fuels, Pyrolysis or gasification of biomass)	C10L5/00 OR C10L5/40 OR C10L5/41 OR C10L5/42 OR C10L5/43 OR C10L5/44 OR C10L5/45 OR C10L5/46 OR C10L5/47 OR C10L5/48 OR C10B53/02 OR C10L9/00 OR C10L1/00 OR C10L1/02 OR C10L1/14 OR C10L1/19 OR C07C67/00 OR C07C69/00 OR C10G OR C11C3/10 OR C12P7/64 OR C10L1/182 OR C12N9/24 OR C12P7/06 OR C12P7/07 OR C12P7/08 OR C12P7/09 OR C12P7/10 OR C12P7/11 OR C12P7/12 OR C12P7/13 OR C12P7/14 OR C02F3/28 OR C02F11/04 OR C10L3/00 OR C12M1/107 OR C12P5/02 OR C12N1/13 OR C12N1/15 OR C12N1/21 OR C12N5/10 OR C12N15/00 OR A01H OR C10B53/00 OR C10J
Geothermal energy	F24T OR F01K OR F24F5/00 OR H02N10/00 OR F25B30/06 OR F03G4/00 OR F03G4/01 OR F03G4/02 OR F03G4/03 OR F03G4/04 OR F03G4/05 OR F03G4/06 OR F03G7/04
Ocean energy	F03G7/05

Table A2. The classification of southern and northern provinces in China.

Regions	**Provinces**
Southern China	Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan,
Northern China	Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shandong, Henan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang

Table A3. Abbreviation list

Abbreviations			
COP26	The 26th United Nations Climate Change Conference	CEE	Carbon emission efficiency
IV-GMM	The instrumental variable-generalized method of moments	CO_2	carbon dioxide
CAICT	China Academy of Information and Communications Technology	NEA	National Energy Administration
CDM	Clean Development Mechanism	SBM	Slacks-based measure
DEA	Data envelopment analysis	GTFEE	Green total factor energy efficiency
R&D	Research and development	DMUs	Decision-making units
IPC	International Patent Classification		

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Tables

Table 1. Indicators for measuring carbon emission efficiency.

	Indicators	**Definition**	**Unit**	**Sources**
Input	Labor force	Number of employees	10000 people	NBS (2022c)
	Capital stock	Total fixed assets investment	100 million yuan	NBS (2022c)
	Energy input	Total energy consumption	10000 tons	NBS (2022a)
Desirable output	Economic output	Real gross domestic product	100 million yuan	NBS (2022c)
Undesirable output	CO_2 emissions	CO_2 emissions	Million tons	Shan et al. (2020) and Shan et al. (2018)

Table 2. Indicators for measuring the Internet economy.

Category	Indicator	Units	Sources
Internet penetration	Netizen penetration rate	%	CINIC (2022)
	Total number of internet users	100000	NDRC (2022)
Internet infrastructure	IPv4 proportion	%	CINIC (2022)
	CN domain names	-	CINIC (2022)
	Long-distance fiber length	10000km	NBS (2022c)
	Number of internet ports	10000	NBS (2022c)
Internet information resources	Average page bytes	kb	CINIC (2022)
	Average number of websites owned by a company	-	NBS (2022c)
Internet application	Express business volume	10000	NBS (2022c)
	Total telecom business revenue	100 million yuan	NBS (2022c)

Table 3. Descriptive statistics of the variables (after logarithm).

Variable	Obs.	Mean	Std. dev.	Min	Max
lnCEE	360	-0.8556	0.3480	-1.7894	0.0232
lnINT	360	-2.0340	0.7049	-3.7401	-0.3740
lnPGDP	360	1.6242	0.3415	0.8043	2.5195
lnIND	360	0.0335	0.3742	-0.6405	1.5880
lnRD	360	0.1718	0.6253	-1.6094	1.8050
lnURB	360	-0.6563	0.2452	-1.2927	-0.0882
lnHUM	360	6.6935	0.0776	6.4161	6.8249
lnRETI	360	7.2685	1.3920	3.3552	10.5314
lnEM	360	4.1298	0.4439	1.5916	5.0300

Table 4. Estimation results of the benchmark model.

Dependent variable: *lnCEE*					
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
lnINT	0.141***				
	(0.0327)				
lnINT1		0.106***			
		(0.0405)			
lnINT2			0.054**		
			(0.0241)		
lnINT3				0.015	
				(0.0740)	
lnINT4					0.098***
					(0.0203)
lnPGDP	0.420***	0.367***	0.431***	0.515***	0.301***
	(0.0604)	(0.0870)	(0.0744)	(0.0823)	(0.0723)
lnIND	0.102***	0.127***	0.105***	0.100***	0.141***
	(0.0320)	(0.0341)	(0.0379)	(0.0331)	(0.0343)
lnRD	0.133***	0.195***	0.162***	0.199***	0.103***
	(0.0290)	(0.0272)	(0.0350)	(0.0287)	(0.0341)
lnURB	-0.135	-0.115	-0.013	-0.095	0.078***
	(0.1003)	(0.0938)	(0.0985)	(0.0921)	(0.0959)
_Cons	-1.348***	-1.399***	-1.454***	-1.767***	-0.958***
	(0.1526)	(0.2173)	(0.2087)	(0.2401)	(0.2101)
Kleibergen-Paap rk LM statistic	84.082	86.880	274.334	44.318	71.438
P-value of Kleibergen-Paap rk LM statistic	0.0000	0.0000	0.0000	0.0000	0.0000
Kleibergen-Paap rk Wald F statistic	1197.133	342.360	1565.888	36.166	392.920
P-value of Hansen J statistic	0.8630	0.4269	0.5742	0.7598	0.1461
Obs.	300	300	300	300	300

Notes: ***, **, and * indicates statistical significance at 1%, 5% and 10%, respectively. Standard errors are reported in parentheses.

Table 5. Estimation results of robustness checks.

Dependent variable: *lnCEE*					
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
lnINT	0.117***	0.195***	0.174**	0.146***	0.261***
	(0.0266)	(0.0450)	(0.0771)	(0.0326)	(0.0345)
lnPGDP	0.521***	0.381***	0.137	0.416***	0.462***
	(0.0518)	(0.0818)	(0.1826)	(0.0609)	(0.0516)
lnIND	0.092***	0.111***	0.054	0.123*	0.095***
	(0.0296)	(0.0387)	(0.0751)	(0.0739)	(0.0320)
lnRD	0.099***	0.116***	0.179**	0.120***	0.030
	(0.0272)	(0.0346)	(0.0717)	(0.0307)	(0.0290)
lnURB	-0.107	-0.190*	-0.098	-0.097	-0.169*
	(0.0814)	(0.1092)	(0.3515)	(0.1019)	(0.0930)
_Cons	-1.553***	-1.226***	-0.691	-1.768***	-1.195***
	(0.1265)	(0.1968)	(0.5407)	(0.3217)	(0.1271)
Kleibergen-Paap rk LM statistic		49.064	22.227	84.735	93.411
P-value of Kleibergen-Paap rk LM statistic		0.0000	0.0000	0.0000	0.0000
Kleibergen-Paap rk Wald F statistic		397.845	568.750	1148.911	288.747
P-value of Hansen J statistic		0.2935	0.9546	0.8575	0.000
Obs.	360	180	60	300	360

Notes: ***, **, and * indicates statistical significance at 1%, 5% and 10%, respectively. Standard errors are reported in parentheses.

Table 6. Results of the mediating effects.

Dependent variable:	***lnCEE***	***lnHUM***	***lnCEE***	***lnRETI***	***lnCEE***	***lnEM***	***lnCEE***
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
lnINT	0.141*** (0.0327)	0.032*** (0.0051)	0.099*** (0.0340)	0.352*** (0.0583)	0.119*** (0.0340)	-0.286*** (0.0356)	0.090*** (0.0333)
lnHUM			1.347*** (0.2474)				
lnRETI					0.063*** (0.0218)		
lnEM							-0.180*** (0.0406)
lnPGDP	0.420*** (0.0604)	-0.004 (0.0106)	0.425*** (0.0590)	2.411*** (0.1662)	0.268*** (0.0788)	0.130 (0.0937)	0.442*** (0.0543)
lnIND	0.102*** (0.0320)	-0.024*** (0.0073)	0.133*** (0.0330)	-0.190** (0.0828)	0.114*** (0.0321)	-0.681*** (0.0679)	-0.021 (0.0390)
lnRD	0.133*** (0.0290)	-0.020*** (0.0063)	0.159*** (0.0291)	0.992*** (0.0861)	0.071** (0.0341)	-0.070 (0.0568)	0.121*** (0.0270)
lnURB	-0.135 (0.1003)	0.212*** (0.0167)	-0.419*** (0.1115)	-1.315*** (0.2281)	-0.051 (0.1052)	0.196 (0.1360)	-0.100 (0.0954)
_Cons	-1.348*** (0.1526)	6.915*** (0.0263)	-10.662*** (1.7354)	3.108*** (0.4123)	-1.543*** (0.1717)	3.495*** (0.2137)	-0.716*** (0.2078)
Kleibergen-Paap rk LM statistic	84.082	84.082	80.954	84.082	86.732	84.082	94.890
P-value of Kleibergen-Paap rk LM statistic	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Kleibergen-Paap rk Wald F statistic	1197.133	1197.133	994.912	1197.133	1085.715	1197.133	911.865
P-value of Hansen J statistic	0.8630	0.5845	0.6838	0.9244	0.8303	0.5987	0.9945
Obs.	300	300	300	300	300	300	300

Notes: ***, **, and * indicates statistical significance at 1%, 5% and 10%, respectively. Standard errors are reported in parentheses.

Table 7. Quantile panel regression.

Dependent variable: ln*CEE*					
Variable	**Q10**	**Q25**	**Q50**	**Q75**	**Q90**
lnINT	0.128***	0.061	0.089*	0.130***	0.098***
	(0.0408)	(0.0547)	(0.0519)	(0.0210)	(0.0351)
lnPGDP	0.566***	0.504***	0.436***	0.585***	0.653***
	(0.0760)	(0.0493)	(0.1164)	(0.0446)	(0.0902)
lnIND	0.174***	0.174***	0.065	0.022	0.056
	(0.0538)	(0.0273)	(0.0688)	(0.0275)	(0.0555)
lnRD	0.132**	0.176***	0.161***	0.022	0.022
	(0.0509)	(0.0509)	(0.0561)	(0.0314)	(0.0446)
lnURB	-0.394***	-0.391***	-0.198	0.070	0.254*
	(0.1400)	(0.0734)	(0.1845)	(0.0861)	(0.1378)
_Cons	-2.063***	-2.000***	-1.547***	-1.342***	-1.294***
	(0.2271)	(0.1617)	(0.2766)	(0.1032)	(0.1896)

Notes: *, **, and *** represent 10%, 5%, 1% levels of statistical significance, respectively. Standard errors are reported in parentheses. The bootstrap value is set to 500.

Table 8. Estimation results of heterogeneity analysis.

Dependent variable: ***lnCEE***		
Variable	**Southern China**	**Northern China**
lnINT	0.104***	0.034
	(0.0325)	(0.0482)
lnPGDP	0.204**	0.699***
	(0.0817)	(0.0854)
lnIND	0.061	-0.074*
	(0.0514)	(0.0432)
lnRD	0.001	0.282***
	(0.0357)	(0.0421)
lnURB	0.377***	-0.083
	(0.1105)	(0.1270)
_Cons	-0.621***	-2.085***
	(0.1826)	(0.2259)
Kleibergen-Paap rk LM statistic	53.712	43.912
P-value of Kleibergen-Paap rk LM statistic	0.0000	0.0000
Kleibergen-Paap rk Wald F statistic	728.706	382.683
P-value of Hansen J statistic	0.4128	0.6863
Obs.	150	150

Notes: ***, **, and * indicates statistical significance at 1%, 5% and 10%, respectively.

Standard errors are reported in parentheses.

Figures

Fig.1. Spatial distribution of China's CEE and Internet development indexes for selected years.

Fig.2. The internal mechanism between the Internet economy and CEE.

Fig.3. Change in panel regression coefficients.

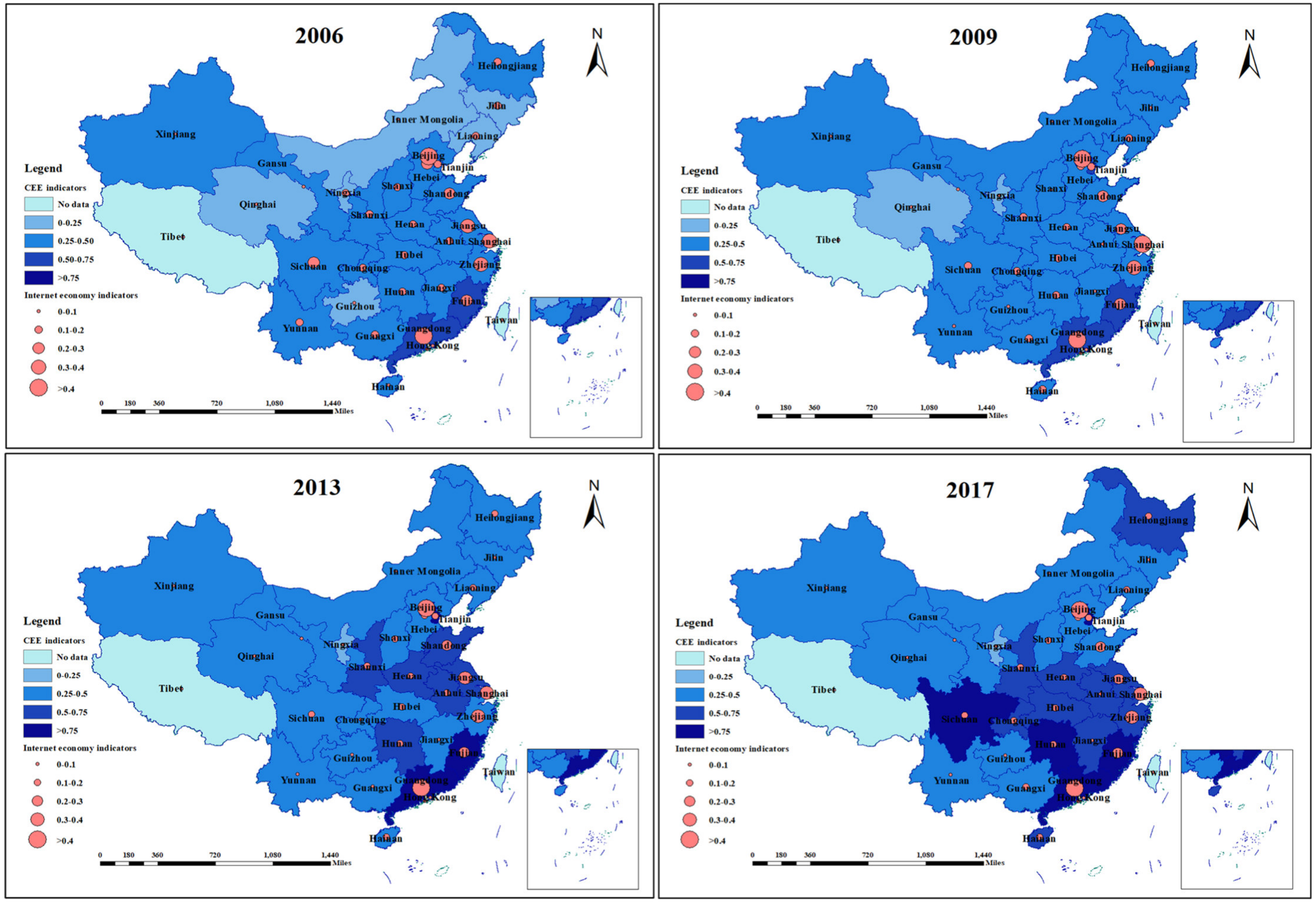

Fig.1. Spatial distribution of China's CEE and Internet development indexes for selected years.

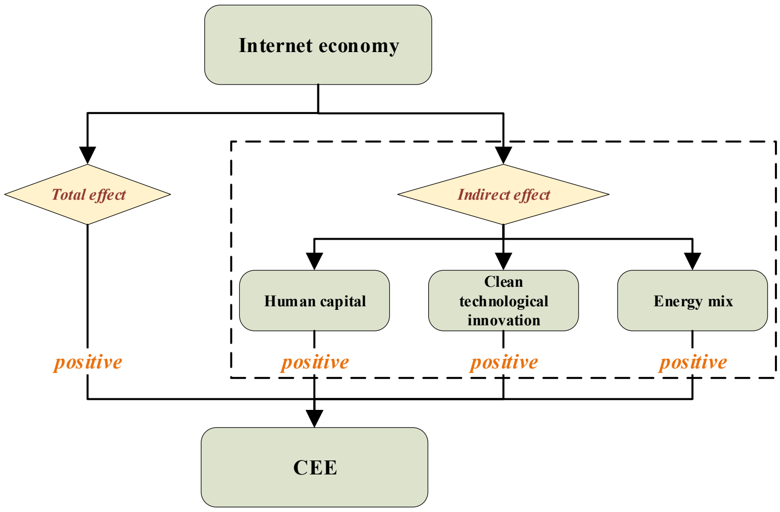

Fig.2. The internal mechanism between the Internet economy and CEE.

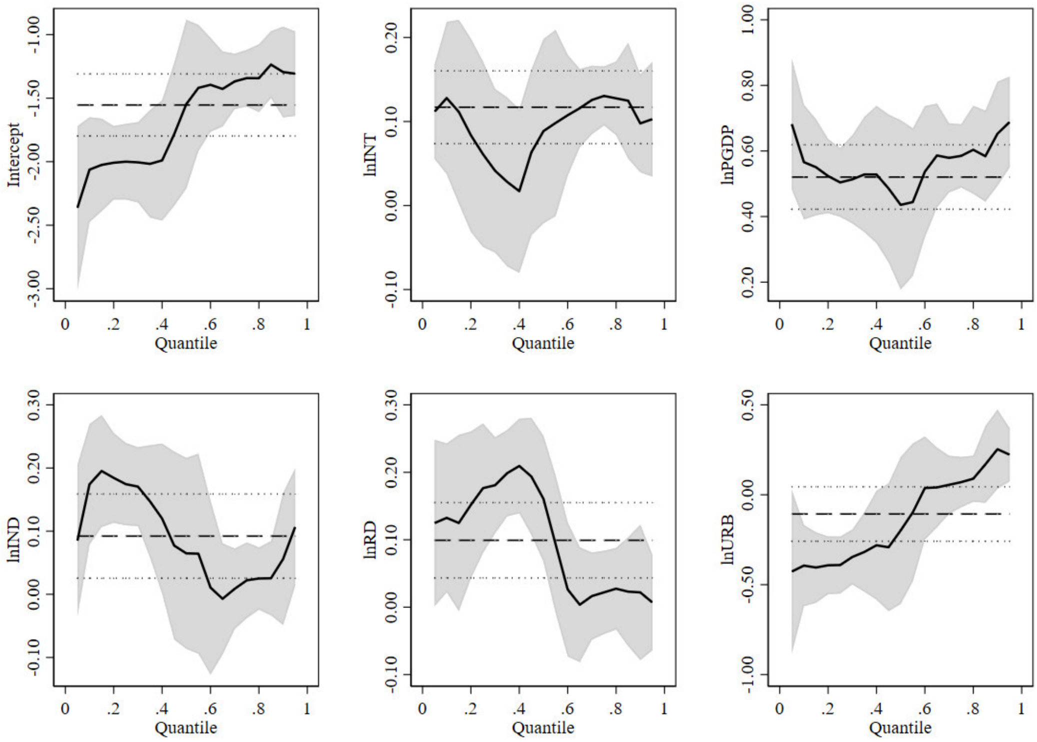

Fig.3. Change in panel regression coefficients.

Notes: The x-axis represents the conditional quantiles and y-axis denotes the coefficients.