Quantifying the Impact of Intelligence on Energy Efficiency in China

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Abstract—To boost energy efficiency and assure more wise resource allocation, China has developed a manufacturing power strategy, meaningfully implemented green manufacturing and intelligent manufacturing projects, and promoted the green, intelligent, and high-end manufacturing sector. China's illogical energy structure, significant pollution problems, low energy consumption efficiency, and other crucial challenges are now seriously impeding the integration of China's industrialization and informationization processes. Investigating whether intelligence may have a direct impact on energy efficiency is beneficial in order to attain intelligent energy and smart energy in the era of intelligent development. Using panel data from 30 provinces from 2011 to 2019, this study constructs a fixed-effects model to evaluate the aggregate and mediating impacts of energy efficiency. The findings demonstrate that intelligence may greatly increase energy efficiency, but the effect is defined by geographical variability, as opposed to improving energy efficiency through fostering technical advancement.

1. Introduction

The advancement of social intelligence will undoubtedly have a significant influence on human productivity and lifestyle, much like how economic structure is being improved and optimized and artificial intelligence is being merged with a variety of businesses. Cloud computing, big data, artificial intelligence, and other elements of the new technological revolution are exploding and are increasingly fueling economic development in many countries[1]. In the framework of the current technological revolution, improvements in artificial intelligence technology will have a substantial influence on the social economy, making intelligent advance a strategic focal point[2]. Information technology is more important in this setting for economic progress. By 2025, robots will do 50% of all work globally, according to a study by the World Economic Forum, and the robot revolution will also lead to the creation of 97 million additional employment. In 2021, China manufactured 366,000 industrial robots. Since then, robotics has expanded to 52 important industries, including the medical, light industrial, petrochemical, electronics, and automotive sectors. It is important to support and develop developing digital sectors including big data, blockchain, artificial intelligence, and high-end green manufacturing[3]. According to China's Vision 2035 and the 14th Five-Year Plan, we should also create innovative service manufacturing models and fully execute green manufacturing and intelligent manufacturing initiatives. The world's top producers are aware of the harmful effects intelligence has on the economy. These countries have put policies to enhance intelligence development as an industrial transition and upgrading strategy in place to handle the shifting nature of the global economy and the shortage of resources.

But as the industrial process quickens, carbon emissions rise year after year and energy consumption keeps rising, making the energy issue a major barrier to human advancement. Global industrial production and energy combustion produced 36.3 billion tons of carbon dioxides in 2021, an increase of 6% from the previous year; coal was responsible for 15.3 billion tons of those emissions, or more than 40% of all carbon dioxide emissions worldwide.Our government is actively promoting the reform of the economic growth model, converting from a crude economic growth model to an intensive economic growth model, and making energy conservation and emission reduction a national strategy[4] in order to ensure healthy and sustainable economic and social development and to deal with global pollution. The Chinese government adopted "double control" on energy intensity and consumption in the 12th Five-Year Plan and suggested clean and efficient as the direction of structural adjustment.According to China's 13th Five-Year Plan, promoting the clean and efficient development and use of coal is the primary task and cornerstone of energy transformation and development[5], and the main reliance on accelerating institutional reform and technological innovation to promote sustainable energy development. Therefore, controlling energy consumption and increasing energy efficiency are crucial for attaining

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sustainable regional and global economic development[6].

The incorporation of new technologies into energy consumption is made possible by intelligence, which fosters innovation and business energy efficiency. Intelligent technology enables business employees to make more effective and reliable decisions based on the learning, reasoning, association, and problem-solving of known knowledge[7]. As the level of intelligent technology improves, these capabilities of business employees will continue to improve, promoting the creation of knowledge and knowledge absorption within the enterprise, promoting the technological progress of the enterprise, and promoting the improvement[8].At the same time, intelligent and networked collaborative manufacturing may lower the cost of information exchange and transmission across business, support business technical advancement, increase business capacity for innovation, and boost business energy efficiency. The advancement of technology is one way that intelligence may increase the energy efficiency of an organization. On the other hand, intelligence can also increase the energy efficiency of an organization by enhancing its technical and production efficiency.

2. Models Materials and Methods

As a general advancement in technology, intelligence uses self-determination and deep learning through technologies like artificial intelligence, cloud computing, and big data, and has the capacity to think like a human in order to quickly and accurately monitor and configure processes like the production, delivery, and trading of energy, as well as to construct energy networks using interconnection systems to distribute limited energy resources to businesses in need of it.In addition, blockchain technology provides transparent and open energy information for business, assisting them in obtaining timely and accurate information on energy quality, production, and management[9]. Intelligence automates energy production through robotic equipment and improves energy efficiency[10]; at the same time, intelligence facilitates enterprise communication, and video calls and online meetings can improve the production and management efficiency of energy and other factors[11].The three theories presented in this study are as follows: H1: Intelligence contributes to increased energy efficiency; H2: Intelligence encourages increased technical advancement; H3: To increase energy efficiency, there exist geographical variance in intelligence.

2.1 Model Creation

This study builds a benchmark regression model of the relationship between IQ and energy efficiency to test Hypothesis 1.

$$EE_{it} = \alpha_0 + \alpha_1 IDL_{it} + \alpha_2 X_{it} + \omega_i + \eta_t + \mu_{it} \qquad (1)$$

When a province is denoted by i, year is denoted by t, and the explanatory variable EE stands for energy effectiveness. IDL stands for intelligence degree, a collection of control variables called X, as well as the symbols for individual fixed effects, temporal fixed effects, and a random disturbance term, all have the potential to have an impact on energy efficiency.

This work employs instrumental variables to build a two-stage least squares regression on the panel data, with the following one-stage equation, in order to further examine the relationship between intelligence and energy efficiency and to solve the endogenous problem.

$$IDL = \beta_0 + \beta_1 V_{it} + \beta_2 X_{it} + \omega_i + \eta_t + \mu_{it} \qquad (2)$$

V stands for the chosen instrumental variable. The mediating impact of intelligent energy efficiency increase is examined to further evaluate hypothesis 2. Equation (1) serves as the foundation for future construction of the mediating effect model[12].

$$\mathrm{M}V_{it} = \gamma_0 + \gamma_1 IDL_{it} + \gamma_2 X_{it} + \omega_i + \eta_t + \mu_{it} \qquad (3)$$

$$EE_{it} = \delta_0 + \delta_1 IDL_{it} + \delta_2 MV_{it} + \delta_3 X_{it} + \omega_i + \eta_t + \mu_{it} \qquad (4)$$

Where MV stands for the mediating factor. We first regressed equation (1) to test for the mediating effect; if α1 is positive, it means that the increase in intelligence has a substantial impact on the improvement of energy efficiency. After that, we perform a regression analysis on equation (3), and if γ1 is significantly positive. It means that intelligence considerably affects the mediating variable. Finally, the regression of equation (4) shows that the direct effect of intelligence on increased energy efficiency is δ1 and the indirect effect is δ2×γ 1.According to the assumption that δ2 is significantly positive, if δ1 is not significant, it means that there is no mediating effect; if δ1is significant and decreases from the value in equation (1), it means that there is a partial mediating effect; otherwise, there is no mediating effect. The proportion of the mediating effect is δ2×γ1 /α1.

2.2 Variable Description

Due to the absence of consistent criteria for evaluating energy efficiency in current research, the explanatory variable is EE (energy efficiency), according to the pertinent literature[13][14]. This article uses the conventional approach of calculating energy efficiency, which is easy to use and can easily show whether energy is successfully used in the socio-economy, i.e., the ratio of real GDP (with 2011 as the base year) to total energy consumption is used as the explanatory variable. The greater the value, the higher the source efficiency and the greater the output per unit of energy consumption.

The primary explanatory variable is IDL (intelligence development level), which measures how well China's diverse industries are now integrated with intelligence. Artificial intelligence research has steadily risen as a result of the creation of diverse models and the accessibility of data. This work creates the intelligence index system and improves the design of indexes in order to assess the intelligence index of each prefecturelevel city. This study uses the ratio of post and telecommunications business volume to GDP in each region to measure, and also gives weights to each basic index to finally calculate the intelligence level of each region because post and telecommunications communication increases the degree of informatization[15].

The logarithm of real GDP is used to calculate LnGDP (level of economic development), with 2011 serving as the base year; IL (level of industrialization) is measured in nominal terms across areas in the current year and is stated as the ratio of industrial growth to GDP; In order to compare foreign direct investment (LnFDI) among areas in the current year, the logarithm of the amount of FDI per capita is used, and HCL (Human Capital Level) is given as the average number of years spent in school [16] .

The mediating variable chosen in this study to test hypothesis 2 is technological progress (SI), which entails higher output, higher efficiency, and lower energy consumption, all of which are favorable to the combination of production and intelligence, as well as lower environmental pollution and energy consumption. Patents for inventions are also subject to more rigorous state sector audit, which reflects the region's core innovation capacity and has a higher level.To gauge each province's technical development, a ratio of all granted patents was used (SI).

This study uses research data from the years 2011 to 2019 with a total sample of data drawn from 30 provinces. The major sources of data were the EPS database, China Urban Statistical Yearbook, China High Technology Industry Statistical Yearbook, China Science and Technology Statistical Yearbook, China Industrial Statistical Yearbook, National Financial Statistics of Cities and Counties. Table 1 display descriptive statistics for the primary variables. In the study, to reduce the impact of some outliers on the estimation findings, all continuous variables were empirically estimated using tailing treatment.

TABLE I DESCRIPTIVE STATISTICS RESULTS

Variable	Variable Symbol	Observed value	Max	Min	Mean	Std
Energy Efficiency	EE	270	3.8012	0.4863	1.5843	0.6526
Level of Intelligence	IDL	270	0.9327	0.0212	0.2573	0.1174
Level of Economic Development	LnGDP	270	11.4657	7.4214	9.7876	0.8476
Level of Industrialization	IL	270	0.5562	0.1133	0.3257	0.0835
Foreign Direct Investment	LnFDI	270	9.0488	1.6553	6.4879	1.3334
Level of Human Capital	HCL	270	12.7176	7.5135	9.2048	0.9021
Technological Advancement	SI	270	104.9737	1.2878	19.0776	20.8719

3. Results & Discussion

In this research, a panel fixed-effects model is employed to examine how intelligence affects energy efficiency. The results of the baseline regression using equation (1) to test proposition 1 are shown in Table 2. With or without the addition of control variables, controlling for time and individual fixed effects, the results demonstrate that the test coefficient of the level of intelligent development is significantly positive at the 1% level, demonstrating that intelligent development significantly improves energy efficiency and hypothesis 1 is confirmed. According to the predicted coefficients, energy efficiency increases by 0.874 units for every unit rise in the level of intelligent development.

Table II Results of the baseline regression

Variable	(1) EE	(2) EE
IDL	0.892*** (0.312)	0.874*** (0.354)
LnGDP		-0.009*** (0.427)
IL		0.215 (0.175)
LnFDI		0.082* (0.042)
HCL		0.068* (0.036)
Constant term	0.812*** (0.090)	0.492** (4.747)
Individual effect	controlled	controlled
Time effect	controlled	controlled
Observed value	270	270
R2	0.792	0.812

Notes: (1) ***, **, * indicate statistical values significant at 1%, 5%, and 10% significance levels, respectively; (2) values in parenthesis are standard errors.

This paper bases at the start of the study in 2013, then performs model estimation. The results still show positive estimated coefficients, which suggests the robustness of the study findings. This is done in consideration of the rapid development of intelligence in China, particularly from 2013 onwards. The data from the four municipalities of Beijing, Shanghai, Tianjin, and Chongqing are excluded from the total sample and regressed; the results still support hypothesis 1[18] because different regions in China have different resource endowments and inconsistent levels of economic development, which can affect the effect of intelligence on energy efficiency.

This paper divides the total sample into three work samples in the central, western, and eastern regions and uses the method of sub-sample regression for regional heterogeneity analysis. The empirical results are shown in Table 3. Due to the regional heterogeneity in the degree of influence of intelligence on energy efficiency improvement in each region in China due to the variability of the development level and the resource endowment of each region, there may be regional heterogeneity in each region.The findings demonstrate that the central and eastern regions' levels of intelligent development are significantly positive at the 1% level, while the western region's levels are not significant. This confirms claim 3 that the central and eastern regions' levels of intelligence are more significant in increasing energy efficiency than the western region. In addition to having a foundation of first-mover advantages in location, talent, technology, etc., the eastern area has a greater degree of economic development and earlier

development of intelligence, which supports the regional economy.The process of intelligence working on energy efficiency is accelerated by development's quick pace. Additionally, the country's primary energy, raw materials, and mineral resources are supplied from the central area, and intellect is applied early. The western region is less capable of managing environmental pollution than the eastern and central regions due to the western region's remoteness from port, technological innovation, foreign direct investment, and high-end talent's preference for coastal cities. Additionally, the western region's role in energy efficiency is less effective than that of the eastern and central regions due to the western region's complex topography.

Table III Results of regional heterogeneity estimation

Variable	Central Region	Western Region	East Region
IDL	0.912*** （0.271）	0.462 （0.275）	0.964*** （0.273）
LnGDP	1.237* （0.624）	-0.524 （0.352）	0.142* （0.694）
IL	-0.684 （0.610）	2.104*** （0.361）	0.458 （0.625）
LnFDI	-0.007* （0.018）	0.402*** （0.061）	0.027* （0.058）
HCL	0.048** （0.045）	0.010** （0.014）	0.216* （0.146）
Constant term	-9.37*** （6.372）	1.256** （3.87）	1.742** （5.372）
Individual effect	controlled	controlled	controlled
Time effect	controlled	controlled	controlled
Observed value	72	99	99
R^2	0.927	0.864	0.943

The mediating effect test is used in this study to determine if technical advancement have a mediating role in the improvement of energy efficiency brought on by intelligence. The results are displayed in Table 4 below. The findings indicate that intelligence considerably increases energy efficiency, as seen in Table 4 (1). The coefficients in Table (2) are strongly positive, indicating that intelligence plays an important role in fostering technical advancement. In turn, intelligence promotes technological advancement, which enhances the added value of goods and causes an industry to rise up the value chain.Through technical advancement, intelligence accomplishes the best distribution of energy, other resources, and production variables, raising the bar for the green sector. The results in Table 4 (3) demonstrate that there is a partial mediating effect of technological progress in the promotion after including the mediating variable technological progress in the baseline regression model. The coefficient of the mediating variable is significantly positive, the coefficient of technological progress is 0.058, and the coefficient of the core explanatory variable intelligence is 0.592, which decreases in comparison with the total effect of 0.874.

Table IV Estimated results of intermediate effects

Variable	（1）EE	（2）SI	（3）EE
IDL	0.874*** （0.354）	52.391*** （13.421）	0.592*** （0.178）
SI			0.058** （0.017）
LnGDP	-0.009*** （0.427）	-20.785 （16.421）	0.034* （0.493）
IL	0.215 （0.175）	21.327 （12.271）	-0.021 （0.627）
LnFDI	0.082* （0.042）	2.471 （1.238）	0.056* （0.042）
HCL	0.068* （0.036）	0.732 （2.135）	0.072* （0.028）
Constant term	0.492** （4.747）	172.572 （125.780）	-0.537 （4.873）
Individual effect	controlled	controlled	controlled
Time effect	controlled	controlled	controlled
Observed value	270	270	270
R^2	0.812	0.736	0.809

4. Conclusions

Using panel data from 30 provinces between 2011 and 2019, this study assesses the overall advantages and mediating impacts of intelligence on energy efficiency. The findings indicate that, first, intelligence contributes to increased energy efficiency. However, there is regional variation in this impact, and intelligence's contribution to increased energy efficiency is more pronounced in the eastern and central areas than in the western region. Second, by encouraging technical advancement, intelligence growth may boost energy efficiency. Therefore, it is essential to fully utilize intelligence's contribution to the enhancement of energy efficiency and to strengthen the development of intelligent supporting infrastructure across diverse regions. Infrastructure, supporting technologies, and organizational structure all have a role in how intelligence is enhanced, thus business should be actively pushed to raise the bar on intelligence. Enterprises can build 5G base stations, data storage devices, and intelligent robot intelligent hardware to safeguard their production and transportation efficiency[19]. Improve the carbon trading market, enhance the technology exchange between the eastern and western regions, effectively direct the advanced businesses and talents in the central and eastern regions to support the western region in a targeted manner, and adopt big data, cloud computing, artificial intelligence, and other digital technologies to predict regional carbon emissions.

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