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Artificial Intelligence Impact on Energy Efficiency of Firms: Evidence from Firm-level Data in China

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ABSTRACT

This paper employs the robot application data from the International Federation of Robotics and China's micro firm-level data to empirically investigate the impact of artificial intelligence on the energy efficiency of firms. Artificial intelligence has a positive and significant impact on improving Chinese firms' energy efficiency. Controlling the endogeneity issues, the results show robust. Artificial intelligence affects the energy consumption of enterprises through scale, structural, and efficiency effects. Structural and efficiency effects are greater than the impact of scale effects. Therefore, artificial intelligence saves energy consumption and improves energy efficiency.

Keywords: artificial intelligence, energy efficiency, total factor productivity, scale effects, structural effects, efficiency effects

NONMENCLATURE

Abbreviations	
AI	Artificial intelligence
IFR	International Federation of Robotics
TFP	Total factor productivity
Symbols	
t	Year
i	Enterprise
j	Industry
α	Individual fixed effects
δ	industry-level fixed effects
ε	random error term

1. INTRODUCTION

Energy is an essential driving force for economic development and the material basis for the development of human society. The current problems that each country needs to face and try to solve are how to improve the energy efficiency of enterprises and realize energy transformation and economic development from high-speed growth to high-quality development. Innovation-led development paves the way for achieving green and sustainable development of the world economy. Artificial Intelligence (AI), which can drive the transformation and upgrading of industries will undoubtedly become an important module for countries to enhance the core competitiveness. In 2015, China officially proposed the "robot revolution", and its AI industry began to enter a rapid development stage. Studying the impact of this development in AI on the enterprises' energy efficiency is not only conducive to clarifying how AI improves the enterprises' energy efficiency, but also provides a new path to achieve energy reduction and green development.

AI is bringing profound changes to societies, organizations, and individuals. The rapid development of AI has deeply affected firms' behaviors in production and management in various industries. How does AI affect the firm's energy consumption and energy efficiency? What are the mechanisms behind such a relationship? To our best knowledge, there is no relevant research at present, and our study is the first paper to investigate the impact of AI on energy efficiency using large firm-level data. Moreover, the existing research on energy efficiency mostly focuses on the macro level, which disregard the heterogeneity at the firm level. Based on the existing literature, this paper comprehensively uses the robot data provided by the International Federation of Robotics (IFR) and the micro-enterprise data issued by the China Industry Business Performance Database and the China Polluting Enterprise Database to empirically verify the impact of AI on the energy efficiency.

The paper contributes to the present literature in three ways. First, in terms of research issues, most of the existing research on AI focuses on the AI impact on productivity and the substitution effects of labor markets. Also, research on energy efficiency concentrates on the decomposition and traditional influencing factors of energy efficiency. How does the rapid development of new technologies such as AI change the energy efficiency of enterprises? This question deserves our attentions. Second, this paper constructs a large and comprehensive micro dataset that allows us to capture more heterogeneity of firms and micro-level mechanisms. Last but not least, this paper provides an in-depth analysis of the AI applications affecting energy efficiency, which can provide new insights for enterprises to improve energy efficiency. These new insights would help promote the optimization of energy structure, alleviate resource and environmental constraints, realize the close integration of science and technology, energy and economy, and proactively address the global climate change.

The structure of this paper is as follows. The following sections present the related literature review. Section 3 describes the estimation strategy, data sources, and variables. Section 4 shows the basic estimates results and robustness checks, and tests three kinds of mechanisms. And Section 5 concludes the paper.

2. LITERATURE REVIEW

The study is closely related to two strands of literature. The first body of literature is related to studies on the influencing factors of energy efficiency. The price of energy products [1], export learning effect from international trade[2], and urbanization process [3], etc. have been shown to affect energy efficiency.

The second body of literature is the research related to the social and economic effects generated by AI. The current research related to AI focuses on the replacement and impact of industrial robot applications on labor factors [4], the production efficiency improvements[5], etc. The “information technology productivity paradox” argues that although AI brings significant efficiency gains, they benefit only a few large firms, while the utility of other market participants remains the same. However, some other scholars hold the opposite argument, for example, Aghion et al. (2018)[6]found that the application of AI would increase firm productivity and facilitate the acceleration of the automation process, which would lead to a reduction in the use of human labor in the production process, allowing for an increase in the share of capital returns in the economy.

At the intersection of the two fields, the current literature on the impact of AI applications on pollution and carbon emissions is still relatively sparse. The European Electricity Industry Association (Eurelectric) pointed out in the “Distribution Grids in Europe: Facts and Figures 2020” report that the application of AI in the energy system will help improve the efficiency of renewable energy utilization, which is of great benefit to the global energy transition. Eurelectric predicted that in the next five years, about 81% of the world's energy companies will use AI technology, and as the technology continues to advance, energy companies will also benefit from it. As the global digital technology becomes more and more developed, the application scenarios of advanced technologies including AI, 5G, blockchain, etc. will all become more and more extensive and will play a key role in the global action against environmental and climate change.

In terms of data on the measurement of AI, many scholars have used industrial robot density to measure the penetration of AI [7]. This database provided by IFR covers authoritative data on industrial robot applications worldwide based on the application area, robot type and industry branch, and is now widely used in robotics-related research.

In summary, existing studies have investigated energy efficiency from multiple perspectives, such as industrial structure, openness, technological progress and factor markets, and few scholars have deeply considered the impact of AI on energy efficiency. And the literature has mostly focused on the regional or industry level, without using more microdata to study the changes in energy efficiency at the enterprise level. Research based on microdata is conducive to revealing the true behavior of enterprises and is useful to provide insight into possible firm heterogeneity which can better reveal the changes in energy efficiency.

3. RESEARCH DESIGN

3.1 Model

This paper studies the impact of applying industrial robots on the enterprises’ energy efficiency and establishes an econometric model with energy efficiency as the explained variable and AI level as the core explanatory variable. The model is as follows:

$$\ln Efficiency_{ijt} = \beta_0 + \beta_1 \ln Robot_{jt} + \gamma Ctrl_{ijt} + \alpha_i + \lambda_t + \delta_j + \varepsilon_{ijt} \quad (1)$$

where $\ln Efficiency_{ijt}$ represents the energy efficiency of enterprise *i* in industry *j* in year *t*; $\ln Robot_{jt}$ is the core explanatory variable, representing the AI level of industry j; $Ctrl_{ijt}$ are the control variables at the industry or enterprise level, including industrial structure, enterprise scale, enterprise age, export value, energy price, and firm ownership; α_i is individual fixed effects, which indicates firm characteristics that do not change with time; λ_t is year fixed effects; δ_j denotes industry fixed effects; ε_{ijt} is the random error term.

3.2 Variables

Energy efficiency: This study uses energy productivity as an indicator to measure the firm-level energy efficiency of industrial enterprises. The energy productivity (*Efficiency*) of an enterprise is its industrial output value (*Output*) divided by the energy input (*Energy Input*), that is, the industrial output value of the unit energy consumption in an enterprise. Since the China Polluting Enterprise Database no longer publishes coal usage data after 2010, this paper uses the sulfur dioxide (SO2) emissions of industrial enterprises to measure the amount of energy input. Fig.1 shows the trends of energy efficiency of Chinese firms which reveals a stable upward trend within 2005-2014.

Artificial intelligence: This paper uses the density of industrial robot application to measure the AI level. The density of industrial robots at the industry level (*lnRobot_CN*) is the stock of industrial robots released by the IFR divided by the number of employees in the industry each year in logarithm. Fig.2 and Fig.3 compare the annual stock and installation of robots in China (*Operational stock_CN and Installation_CN*) and the US (*Operational stock_US and Installation_US*) within 1998-2019. At the end of 2015, China's robots stock has surpassed that of the US, and it is still in a stage of rapid growth. At the end of 2019, the stock of robots in China reached 782,725 units which is far exceeding that of the US, accounting for 299,674 units.

3.3 **D***ata source*

The enterprise-level SO_2 emissions data comes from the China Polluting Enterprise Database. The source of other enterprise-level data is from the China Industry Business Performance Database. Industry-level AI data is from the IFR database. Industry energy prices and other macroeconomic indicators come from the National Bureau of Statistics, and the data span is 2005-2014.

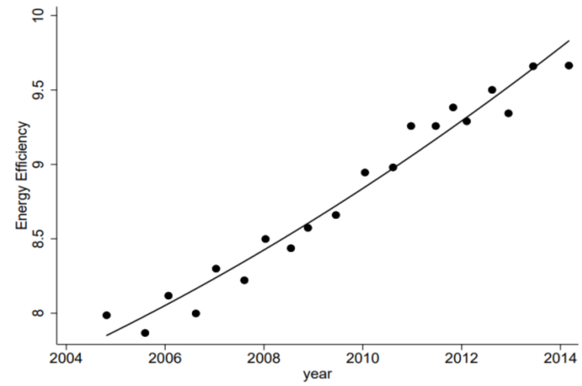

Fig. 1. Trends of China's energy efficiency during 2004-2014

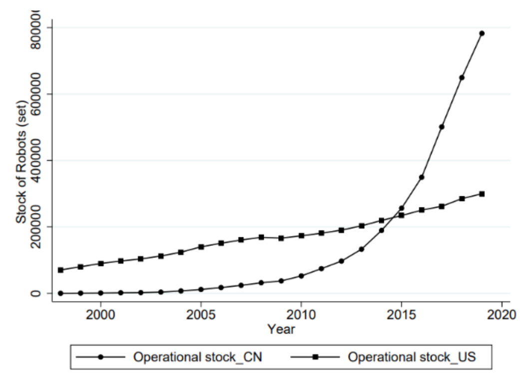

Fig.2. Stock of robots

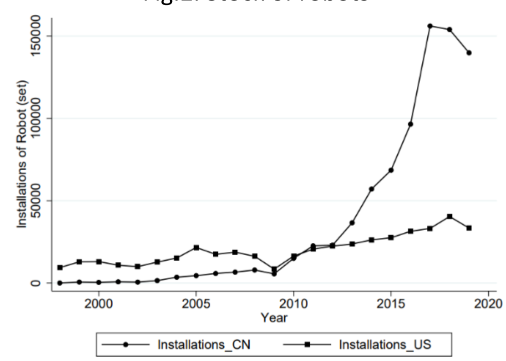

Fig.3. Installations of robots

4. EMPIRICAL RESULTS AND ANALYSIS

4.1 Basic results

Table 1 shows the estimated results of equation (1). Column (1) controls time and firm fixed effects, and column (2) controls time, industry, and firm fixed effects. Results show that the level of AI has a positive and statistically significant effect on energy utilization efficiency at 1% significance level. This result implies the significant and positive effect of the AI on energy efficiency since the industrial robots as a new production factor improve the enterprises' productivity through their own technology and the diffusion and penetration of AI in the production process.

Table 1 Fixed effects estimations

	(1)	(2)
	lnEfficiency	*lnEfficiency*
lnRobot_CN	0.0276***	0.0333***
	(6.08)	(5.33)
lnAsset	0.3359***	0.3346***
	(32.32)	(32.21)
lnExport	0.0087***	0.0087***
	(4.51)	(4.50)
lnPrice	0.0804	0.0383
	(1.59)	(0.74)
Structure	-0.0004	0.0017**
	(-0.93)	(2.18)
Age	-0.0006	-0.0006
	(-0.40)	(-0.39)
Soe	0.0808	0.0854
	(1.48)	(1.57)
Observations	210,710	210,710
R^2	0.867	0.867
Time fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
Industry fixed effects	No	Yes

Notes: The values in parentheses are t-values. *, ** and *** represent the statistical significance level of 10%, 5% and 1% respectively.

4.2 Endogeneity issues

Model (1) may have potential endogeneity. The energy utilization efficiency of the enterprise may simultaneously affect the AI application. Therefore, this paper uses the Instrumental Variable (IV) method to test the impact of AI level on energy efficiency.

Figures 2 and 3 present the installed quantity and stock of industrial robots in the US. Although the stock of robots in China was lower than that in the US before 2015, the stock of robots shows an increasing trend in both countries. In addition, the US leads the world in the use of industrial robots. The impact of the robots' application level in various industries on the labor market in China should only reflect the impact of relatively exogenous technological progress. Moreover, the impact of industrial robot adoption at the US industry level on the labor market in China primarily reflects similar industry technology characteristics (satisfying the relevance requirement of the instrumental variable). This impact is independent of other local factors affecting robot adoption in China (satisfying the exogeneity of the instrumental variable), used as an instrumental variable for robot density at the industry level in China to control the possible endogeneity. Therefore, this paper uses the US industrial robot density to construct instrumental variables.

Table 2 shows the Two-stages Least Square (2SLS) results of the instrumental variable regression. Column (1) represents the result of the first stage, showing the significant and positive correlation of the instrumental variable with the endogenous variable. Column (2) has the regression result of the second stage, showing the positive and significant coefficients of the main explanatory variables at 1% level. This result is consistent with the baseline regression results of Table 1, indicating that AI's significant positive impact on energy efficiency still holds. In the case of "just identification", it is difficult to statistically verify whether the exogenous assumption of instrumental variables is satisfied. Hence, energy efficiency is then regressed on China's AI level and the instrumental variable US AI at the same time. Based on the results in column (3) of Table 2, the instrumental variable has an insignificant effect on energy efficiency, and the AI in China is significant and positive. These results indicate that the instrumental variable only indirectly affects energy efficiency, which proves that our instrumental variable is exogenous.

Furthermore, this paper uses the LM statistic to conduct the under-identification test. The results reject the null hypothesis of "unidentifiable instrumental variables" at 1% significance level. At the same time, the results of the weak instrumental variable test based on the Wald F-statistic show that with only one endogenous variable, the values of both statistics are greater than the critical value at 10% level provided by Stock and Yogo (2005). Hence, this result rejects the null hypothesis of being a weak instrumental variable. The results of the Anderson-Rubin's Wald test reject the null hypothesis that "the sum of endogenous regression coefficients is equal to 0" at 1% level, implying a strong correlation between the instrumental variable and the endogenous variable.

Table 2 Instrumental variable results

	(1)	(2)	(3)
	First-stage	Second-stage	ln*Efficiency*
ln*Robot_CN*		0.0871***	0.0241***
		(21.46)	(3.75)
ln*Robot_US*	0.7734***		0.0112
	(286.13)		(1.45)
control variables	Yes	Yes	Yes
time fixed effects	Yes	Yes	Yes
firm fixed effects	Yes	Yes	Yes
Observations	201,154	201,154	201,154
R^2	0.727	0.050	0.869

Notes: The values in parentheses are t-values. *, ** and *** represent the statistical significance level of 10%, 5% and 1% respectively.

4.3 Robustness tests

We apply alternative energy efficiency indicators, replacing industrial output value with the sales revenue of the enterprise's main business(lnE1), and replacing SO2 emissions with fuel coal consumption (lnE2). We also calculate industry-level AI as the number of robots per 10,000 working hours (lnRobot_CN2). And the results show robust (see Table 3).

Table 3 Robustness tests

	(1) *lnE1*	(2) *lnE2*	(3) *InEfficiency*
ln*Robot_CN*	0.0270***	0.0103**	
	(5.90)	(2.09)	
ln*Robot_CN2*			0.0362***
			(5.62)
control variables	Yes	Yes	Yes
time fixed effects	Yes	Yes	Yes
firm fixed effects	Yes	Yes	Yes
Observations	199,263	75,351	147,305
R^2	0.875	0.877	0.873

Notes: The values in parentheses are t-values. *, ** and *** represent the statistical significance level of 10%, 5% and 1% respectively.

4.4 Heterogeneity analysis

We distinguish enterprise into state owned enterprises (SOEs)and non-SOES, and exporters and non-exporters. Table 4 represents the regression results. Column (1) of Table 4 displays the regression results of non-SOEs. The regression coefficient of non-SOEs is positive and statistically significant at 1% level. This coefficient indicates that AI has significantly promoted the energy efficiency of non-SOEs. Column (2) is the regression results of the SOEs. Although the estimated coefficient of ln*Robot_CN* is insignificant, it is still positive, implying that AI has a positive impact on the improvement of energy efficiency. AI application has a positive and significant relationship with energy efficiency ignorance of whether the enterprises export or not. The coefficient of exporting enterprises is slightly smaller than that of non-exporting enterprises due to the "learning from exporting effect".

Table 4 Heterogeneity test

	(1) non-SOEs	(2) SOEs	(3) non-exporters	(4) exporters
ln*Robot_CN*	0.0272***	0.0137	0.0304***	0.0201***
	(5.96)	(0.27)	(4.44)	(3.20)
control variables	Yes	Yes	Yes	Yes
time fixed effects	Yes	Yes	Yes	Yes
firm fixed effects	Yes	Yes	Yes	Yes
Observations	205,969	4,063	96,458	102,882
R^2	0.867	0.899	0.875	0.895

Notes: The values in parentheses are t-values. *, ** and *** represent the statistical significance level of 10%, 5% and 1% respectively.

4.5 LDMI Decomposition to examine the mechanism of AI effects

This paper uses logarithmic mean Divisia index (LMDI) additive approach to decompose the energy consumption, and the energy consumption is decomposed into three parts: scale, structure, and efficiency effects. The basic idea of this model is:

$$E=\sum_i E_i=\sum_i Q\frac{Q_i}{Q}\frac{E_i}{Q_i}=\sum_i QS_iI_i \tag{2}$$

$$\Delta E_{tot}=E^T-E^0=\Delta E_{act}+\Delta E_{str}+\Delta E_{\text{int}} \tag{3}$$

$$\Delta E_{act}=\sum_i\frac{E_i^T-E_i^0}{\ln E_i^T-\ln E_i^0}\ln\frac{Q^T}{Q^0} \tag{4}$$

$$\Delta E_{str}=\sum_i\frac{E_i^T-E_i^0}{\ln E_i^T-\ln E_i^0}\ln\frac{S_i^T}{S_i^0} \tag{5}$$

$$\Delta E_{int}=\sum_i\frac{E_i^T-E_i^0}{\ln E_i^T-\ln E_i^0}\ln\frac{I_i^T}{I_i^0} \tag{6}$$

where ΔE_{tot} is the change in total energy consumption; ΔE_{act} is the scale effect of increased energy consumption due to the expansion of production scale; ΔE_{str} is the structural effect of energy saving due to the optimization of industrial structure; and ΔE_{int} is the efficiency effect of energy saving due to technological progress. The three components of the decomposition were replaced with the dependent variables in equation (1) of the baseline model for regression estimation, whose results are in 5. The regression coefficient is 3.019, indicating that AI increases energy consumption (rebound effect). However, the coefficient of ΔE_{str} is -0.437, implying that AI reduces energy consumption by adjusting the industrial structure. ΔE_{int} is the efficiency effect with a coefficient of -3.055. Using AI improves technological progress and reduces energy consumption, and the degree of reduction is greater than that of industrial restructuring. Moreover, the regression coefficients of scale and efficiency effects are both significant at 1% level.

Table 5 Regression after LMDI decomposition

	(1) scale effect ΔE_{act}	(2) structural effect ΔE_{str}	(3) efficiency effect ΔE_{int}
ln*Robot_CN*	3.0193***	-0.4371	-3.0547***

	(6.21)	(-0.87)	(-4.46)
control variables	Yes	Yes	Yes
time fixed effects	Yes	Yes	Yes
firm fixed effects	Yes	Yes	Yes
Observations	214,560	178,151	178,151
R^2	0.790	0.708	0.827

Notes: The values in parentheses are t-values. *, ** and *** represent the statistical significance level of 10%, 5% and 1% respectively.

We further use technological progress as a mediating variable to test the mechanism of AI influence on energy efficiency and results are reported in Table 6.

Table 6 Mediating effect test

	(1) *TFP*	(2) *lnEfficiency*
ln*Robot_CN*	0.0046***	0.0259***
	(3.76)	(5.64)
TFP		-0.3431***
		(-8.29)
control variables	Yes	Yes
time fixed effects	Yes	Yes
firm fixed effects	Yes	Yes
Observaions	226,367	207,197
R^2	0.951	0.868

Notes: The values in parentheses are t-values. *, ** and *** represent the statistical significance level of 10%, 5% and 1% respectively.

5. CONCLUSION AND POLICY IMPLICATION

Based on the comprehensive and most disaggregated data from China, this pioneering study empirically tests the AI impact on energy efficiency and analyzes the underlying mechanisms. According to our findings, AI has a significant and positive impact on energy efficiency at the firm level. To overcome the potential endogeneity, the study applies the US industrial robot density as the instrumental variable for further testing, and the above conclusion still holds. Based on heterogeneity analysis, non-SOEs, non-exporters, labor- and capital-intensive enterprises, and SMEs gain greater benefits of energy efficiency promotion from the application of AI. From the mechanism test results, AI increases energy consumption through the scale effect, saves energy consumption through structural and efficiency effects. Since structural and efficiency effects are greater than the scale effect, AI saves energy consumption and improves energy efficiency. Since the scale, structural, and efficiency effects are brought by technological progress from the essence, this paper uses enterprise TFP as a mediator variable to test the linkage between AI and energy efficiency and verify the above impact mechanism.

This study provides rich implications for the governments' energy management and technological development policies. This study shows evidence for policymakers that new technologies such as AI help enterprises change their management methods and production modes to improve energy utilization efficiency, which indicate governments can use AI as a driver for energy reform in developing countries. In addition, enhancing enterprises enthusiasm for R&D and encouraging them to use advanced technologies for production may help enterprises gain great competitiveness and have core competitive advantages. Based on the results, SOEs are often difficult to achieve cost minimization in the actual production and operation process, and their motivation to improve energy efficiency is weaker than that of private enterprises. Therefore, private capital is essential in motivating SOEs to improve energy efficiency and increase their capital return.

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