Artificial Intelligence and Energy Intensity in China's Industrial Sector: Effect and Transmission Channel

Liu, Liang and Yang, Kun and Fujii, Hidemichi and Liu, Jun

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Liang Liu[a] Kun Yang[a] Hidemichi Fujii[b *] Jun Liu[c]

[a] School of Economics and Management, Southeast University, Nanjing, China

[b] Faculty of Economics, Kyushu University, Fukuoka , Japan

[c] China Institute of Manufacturing Development, Nanjing University of Information Science & Technology, Nanjing, China

[*] Corresponding author. Tel.: +81227953216; Fax: +81227954309. E-mail address: hidemichifujii@gmail.com (H. Fujii).

Abstract

The continued development of artificial intelligence (AI) has changed production methods but may also pose challenges related to energy consumption; in addition, the effectiveness of AI differs across industries. Thus, to develop efficient policies, it is necessary to discuss the effect of AI adoption on energy intensity and to identify industries that are more significantly affected. Using data on industrial robots installed in 16 Chinese industrial subsectors from 2006 to 2016, this paper investigates both the effect of AI on energy intensity and the channel through which this effect is transmitted. The empirical results show, first, that boosting applications of AI can significantly reduce energy intensity by both increasing output value and reducing energy consumption, especially for energy intensities at high quantiles. Second, compared with the impacts in capital-intensive sectors (e.g., basic metals, pharmaceuticals, and cosmetics), the negative impacts of AI on energy intensity in labor-intensive sectors (e.g., textiles and paper) and technology-intensive sectors (e.g., industrial machinery and transportation equipment) are more pronounced. Finally, the impact of AI on energy intensity is primarily achieved through its facilitation of technological progress; this accounts for 78.3% of the total effect. To reduce energy intensity, the Chinese government should effectively promote the development of AI and its use in industry, especially in labor-intensive and technology-intensive sectors.

Keywords: artificial intelligence; energy intensity; energy consumption; industrial robot; China

1. Introduction

Energy is the material basis and a strong driver of economic development (Yu and Choi, 1985; Hall et al., 2003; IEA, 2018; Pinzón, 2018). With the acceleration of industrialization, China's economy has displayed unparalleled growth, as has its energy consumption, resulting in severe energy shortages and environmental pollution (Lin and Xu, 2019). In fact, China's energy consumption has exceeded that of the US since 2009, making China the world's largest energy consumer (Dong et al., 2018). However, excessive energy consumption can trigger energy depletion and environmental pollution and thereby severely restrict the sustainable development of China's economy (Chen et al., 2019). With the country facing energy conservation and green transition pressures, reducing energy intensity (i.e., energy consumption in production per unit of output value), as a simultaneous indicator of energy efficiency and economic development, has become one of China's most important tasks (Lin and Tan, 2017). For example, in the 13th Five-Year Plan of China (2016-2020), the Chinese government pledged to reduce energy intensity by at least 15% compared to its 2015 baseline. Therefore, identifying the factors that drive energy intensity in China has become a subject of interest to researchers and to the government in recent years, and clarifying the related influencing factors is helpful for making more effective energy policies (Huang and Chen, 2020).

Artificial intelligence (AI) is one of the most promising technologies currently under development and in deployment (Acemoglu and Restrepo, 2020a). Broadly speaking, AI can be defined as "the capability of a machine to imitate intelligent human behavior"; it drives innovations such as machine learning, deep learning, natural language processing, robots, and others (Cockburn et al., 2018), allowing an incremental number of tasks previously performed by human physical and brain power to be automated and significantly increasing efficiency and productivity (Aghion et al., 2017). China has attached great importance to the development of its AI industry, elevating it to a national strategy. In 2017, the Chinese government published "A New Generation of Artificial Intelligence Development Plan", which guided the development of AI and established the goal of making China the global innovation center of this field by 2030 (Fatima et al., 2020).

These expectations notwithstanding, AI also has some noneconomic consequences that have both positive and negative impacts on energy consumption (Vinuesa et al. 2020), resulting in an uncertain impact on energy intensity. More specifically, by replacing and supplementing the physical and brain power of humans, AI may boost technological progress, and this is the primary driver of AI-related reductions in energy intensity (Haas and Kempa, 2016; Brynjolfsson et al., 2017). Nonetheless, compared to energy-consuming technologies such as machine learning and industrial robotics, the physical and brain power of humans is incredibly efficient and involves far less energy consumption, while AI research and applications such as deep learning platforms demand large amounts of energy (Lu et al., 2018; Vinuesa et al., 2020). For instance, the energy consumption and CO_2 emissions required to train a common natural language processing model are five times higher than those required to produce and use a car (Strubell et al., 2019). This environmental cost is even higher in China, where cloud computing providers derive 65% of the energy they consume from carbon and 22% from renewable energy sources, in comparison to the corresponding values of 38% and 40% in Germany and 27% and 17% in the US (Strubell et al., 2019). In addition, although energy consumption can be reduced by AI to some extent, AI may also increase it due to the enormous stimulus that AI provides to economic growth, causing a rebound effect (Grant et al., 2016). Does application of AI lead to lower energy intensity? Furthermore, what is the mechanism through which AI affects energy intensity?

Considering the industrial sector's enormous energy demand, which accounts for approximately 70% of China's total energy consumption (Luan et al., 2020), this paper takes 16 Chinese industrial subsectors as a sample and investigates the impact of AI penetration on energy intensity and the transmission channel of this effect using data on industrial robot adoption from 2006 to 2016. These data offer us a complete picture of AI in industrial sectors (McElheran, 2018). First, we discuss the effect of AI on energy intensity using the ordinary least squares (OLS), fixed effects (FE), random effects (RE), and feasible generalized least squares (FGLS) methods and further test the separate impacts of AI on industrial output value and energy consumption. Second, we employ the quantile regression (QR) model to analyze the effect of AI on different conditional distributions of energy intensity. Third, the industry heterogeneity in the responses of energy intensity to AI is evaluated by incorporating dummy variables for different factor-intensive sectors. Fourth, using the two-stage least squares (2SLS) model and alternative measurements of AI, we test the robustness of our conclusions. Finally, we further examine the transmission channel connecting AI to energy intensity by introducing technological progress as a mediator variable. Figure 1 shows the research framework of this paper.

(Insert Figure 1 about here)

Most relevant to our study are the papers by Røpke and Christensen (2012), Wang and Han (2016), Zhou et al. (2018) and Avom et al. (2020), which estimate the effect of information and communications technology (ICT) on energy intensity. Unlike prior studies, we attempt to investigate the effect of industrial robot adoption on energy intensity in various industrial sectors. The International Federation of Robotics (IFR) defined "multipurpose manipulating industrial robots" based on the definition provided by the International Organization for Standardization (ISO). According to IFR, an industrial robot is defined in ISO 8373 as an "automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications" (see https://ifr.org/). That is, industrial robots are fully autonomous machines that can be programmed to perform multiple manual tasks without human intervention (Acemoglu and Restrepo, 2020b). This definition excludes software and other automated machines such as textile looms, transport bands and cranes (Acemoglu and Restrepo, 2020b). These capabilities also distinguish industrial robots from innovations developed during the earlier waves of automation and from more conventional ICT, which lack three-dimensional flexible movement capability (Graetz and Michaels, 2018). However, industrial robots may pose a new challenge to energy consumption (Brossog et al., 2015). First, industrial robots depend on ICT, especially on machine learning and deep learning, for programming and control, resulting in high energy demands (Vinuesa et al., 2020). Second, because more energy is needed to drive the hardware apparatus of industrial robots (Pastras et al., 2019), it is crucial to clarify the consequences of AI, especially industrial robots, for energy intensity and the mechanisms of the effect.

The novelty of this study is twofold. First, to the best of our knowledge, this is the first study to investigate the effect of AI on energy intensity. In the previous literature, the positive impacts of AI on economic growth have been widely discussed, while little attention has been paid to the effects of AI on energy consumption and on the environment, effects that are directly related to the sustainability of economic development. Second, we not only investigated the effect of AI on energy intensity by detailing the impact of AI on output value and energy consumption, and the channels through which the impact occurs but also further validated the industry heterogeneity. Industrial characteristics affect the relationship between AI implementation and the change in energy intensity because of technical differences across industries (Fujii and Managi, 2013). The capital equipment and labor requirements for energy savings differ across industries because the types of fuel consumed also differ. Therefore, industrial characteristics provide important information for creating effective AI implementation policies for energy intensity reduction in every industry. Furthermore, we decompose the effect of AI on energy intensity into direct effects and indirect effects via technological progress using the mediation effect model; this decomposition is helpful in allowing us to quantify the transmission channel that connects AI to energy intensity.

2. Literature review

Substantial recent literature has confirmed that energy intensity is driven by technological progress such as the use of more efficient production technologies and newer vintages of capital equipment (technology effects) and changes in the composition of the economy (structural effects) (Fisher-Vanden et al., 2006; Voigt et al., 2014; Huang et al., 2017). In addition, foreign direct investment (FDI) (Huang et al., 2018), research and development (R&D) (Chen et al., 2019), ownership type (Luan et al., 2020), enterprise size (Zhang et al., 2010; Lin et al., 2018), factor endowment (Lan et al., 2012; Bu et al., 2019), and other factors affect how AI changes energy intensity. The impact of AI has been heatedly discussed in recent years from different perspectives, including the points of view of economic growth (productivity) (Bard, 1986; Dirican, 2015; Purdy and Daugherty, 2017; Aghion et al., 2017; Brynjolfsson et al., 2017; Graetz and Michaels, 2018; Kromann et al., 2020; Jung and Lim, 2020; Camiña et al., 2020; Ballestar et al., 2020), innovation (Cockburn et al., 2018; Liu et al., 2020; Li et al., 2020; Yang et al., 2020), employment (Howell, 1985; Edler and Ribakova, 1994; Acemoglu and Restrepo, 2018, 2020a, 2020b; Chiacchio et al., 2018; Dauth et al., 2018; Barbieri et al., 2019; Carbonero et al., 2020; Dekle, 2020; Ballestar et al., 2020; Jung and Lim, 2020), and sustainable economic development (Vinuesa et al., 2020; Machado et al., 2020; Liu et al., 2021).

From an overview of these studies, it is easy to note that energy intensity is heavily influenced by technological progress, which may be triggered by the penetration of AI. That is, the increased use of AI may drive energy intensity by facilitating technological progress. Unfortunately, we found no literature that discusses the effect of AI on energy intensity, including the role of technological progress in this effect. To motivate our paper, we particularly emphasize the technological factors.

2.1. Technologies and energy intensity

The essence of an industrial revolution is the shift from an economy dependent on land resources to an economy dependent on fossil fuels (Wrigley, 1998). Modern technologies, such as steam engines in the 18th century, internal combustion engines since the 19th century and now, increasingly, the use of electricity, are at least partially associated with energy consumption (Koh and Magee, 2018). The global use of fossil fuels as an energy source has increased almost 800-fold since 1750 and approximately 12-fold in the 20th century (Hall et al., 2003). To improve energy efficiency and reduce energy consumption, various technologies for industrial processes, boiler operation, compressed air usage, motor efficiency, heating and lighting and transport applications have been developed and are available (Dyer et al., 2008). For instance, zero- and low-carbon energy technologies use "waste" heat from plants to replace other heat sources, thereby reducing energy consumption in plants by 20-40% (Engineering Council, 1998). Bioenergy and biowaste utilization, including anaerobic digestion, pyrolysis and gasification, is a broad and active field focused on reducing fossil energy dependence (Chowdhury et al., 2018). The percentage of bioenergy in the total energy supply was projected to increase to 12.5% by 2020 and to 15% by 2050 (Chowdhury et al., 2018). Recently, information systems have widely penetrated the energy sector from production to consumption, and traditional energy systems have been digitalized, resulting in intelligent energy systems (Zhou and Yang, 2015). Through the collection of data on energy use and analysis, system design and implementation, information systems can improve the efficiency of energy demand and supply systems and optimize energy distribution and consumption networks; these tasks have developed into a new subfield, energy informatics (Watson et al., 2010). With the increasing amount of data generated and the continuously improving computing power, information systems can predict energy compliance and enable efficient energy management (Heghedus et al., 2018).

However, there is no consensus in the literature on the effect of technological progress on energy intensity. Specifically, on the one hand, a multitude of studies hold that technological progress, especially energy-saving technological progress, increases energy efficiency and reduces energy intensity (Li and Wang, 2017; Huang et al., 2017, 2018; Chen et al., 2019; Huang and Chen, 2020). For example, using data on 30 Chinese provinces for the period 2000 to 2013, Huang et al. (2017) found that technological progress contributes the most to decreases in energy intensity, with a 1% gain in R&D capital stock leading to an energy intensity decrease of approximately 0.07%. Similarly, Huang et al. (2018) pointed out that a 1% increase in China's R&D capital stock is linked to a 0.24% decrease in its energy intensity. On the other hand, quite a few studies argue that although technological progress can reduce energy consumption and improve energy efficiency, lower effective prices cause an energy rebound effect that may trigger a disproportionate decrease in actual energy consumption (Khazzoom, 1980; Shao et al., 2014; Grant et al., 2016; Lin and Zhao, 2016). Therefore, it remains to be determined how technological progress affects energy intensity.

The increasing use of ICT throughout the economy and society has raised great hopes for reducing energy demand (Mickoleit, 2010; Lange et al., 2020). However, like the technological progress literature, the literature on the impact of ICT on energy intensity, which is relevant to our study, also reveals a lack of consensus. On the one hand, early studies, including those of Walker (1986) and Chen (1994), generally concluded that ICT and energy were substitutes for each other and that ICT would reduce energy use. Empirically, some studies find that the application of ICT can promote energy efficiency and productivity and thereby contribute to reducing energy intensity (Røpke and Christensen, 2012; Corbett, 2013; Cai et al., 2013; Wang and Han, 2016; Bastida et al., 2019; Avom et al., 2020). For example, Røpke and Christensen (2012) pointed out that ICT has great potential for reducing energy consumption but that this depends on economic and political conditions. Wang and Han (2016) employed the Driscoll-Kraay econometric method to analyze the effect of ICT on energy intensity and found that ICT investment negatively drives energy intensity. Bastida et al. (2019) showed that ICT-based household energy use interventions can contribute between 0.23% and 3.3% of the EU CO_2 reduction targets for the energy sector.

Conversely, other concerns have been raised about the overall effects of ICT on energy demand (Faucheux and Nicolaï, 2011; Lange et al., 2020). In recent decades, energy consumption and carbon emissions have increased as more and more digital devices have been produced and used (Van Heddeghem et al., 2014; Salahuddin and Alam, 2016; Zhou et al., 2018; Belkhir and Elmeligi, 2018; Lange et al., 2020). According to Van Heddeghem et al. (2014), the electricity consumption of communication networks, personal computers, and data centers has increased by 10%, 5% and 4%, respectively; these increases are larger than the increase in world electricity consumption (3%) over the same period. Similarly, based on OECD panel data for the period 1985-2012, Salahuddin and Alam (2016) found that OECD countries had not yet secured energy efficiency gains from ICT expansion in that period, which saw a 1% increase in the number of internet users and a 0.026% increase in per capita electricity consumption. Using the three-tier structural decomposition analysis approach, Zhou et al. (2018) found that although higher energy efficiency in the ICT sector leads to a slight decrease in energy intensity, structural changes in ICT investment increase energy intensity, and the proliferation of ICT products increases energy consumption by the production process. Lange et al. (2020) analyzed the direct effects of the production, use and disposal of ICT-related products and the effects of ICT on productivity and structure and argued that the hope set on saving energy through ICT has not yet been fulfilled. Instead of reducing energy consumption, ICT has resulted in additional energy use.

2.2. AI and technological progress

In contrast to the conclusions about the effect of technological progress and ICT on energy intensity, there is a general consensus that AI penetration positively affects technological progress (Bard, 1986; Dirican, 2015; Purdy and Daugherty, 2017; Aghion et al., 2017; Brynjolfsson et al., 2017; Graetz and Michaels, 2018; Kromann et al., 2020; Jung and Lim, 2020; Camiña et al., 2020; Ballestar et al., 2020). Theoretically, the impact of AI on technological progress is mainly reflected in the following three aspects (Purdy and Daugherty, 2017). First, AI can create a new virtual workforce to replace labor in performing programmed tasks (Acemoglu and Restrepo, 2020b; Jung and Lim, 2020), enabling “intelligent automation”. The ability of robots to acquire and respond to remotely sensed data and to adaptively control the activities of machine cells represents just some of the basic capabilities they offer. Their inherent versatility emphasizes their advantages over existing stationary automation (Bard, 1986). In a study of industrial robot adoption in 42 countries, Jung and Lim (2020) confirmed this labor-substituting effect. As Brynjolfsson et al. (2017) noted, even if AI were to replace only 2 million car drivers, labor productivity in the US would increase by more than 1.7%. Based on the data on industrial robot adoption in Germany, Dauth et al. (2018) argued that every industrial robot destroyed two manufacturing jobs between 1994 and 2014, representing almost 23% of the overall decline in manufacturing employment in Germany or approximately 275,000 jobs, but that robots do increase labor productivity. Dekle (2020) also demonstrated a positive significant productivity effect following the introduction of industrial robots in Japan.

Second, AI complements and enhances the skills and capabilities of human physical and brain power. Using data on industrial robots in 17 countries from 1993 to 2007, Graetz and Michaels (2018) found that the contribution of the increasing number of industrial robots to annual labor productivity growth is approximately 0.36%, accounting for 15% of total productivity growth, and that their contribution to the growth of total factor productivity is 0.26%. According to Kromann et al. (2020), industrial robots contribute to increasing total factor productivity by more than 5% in 9 countries. Along the same lines, Camiña et al. (2020) examined the relationship between the use of industrial robots and long-term productivity gains in Spanish industrial firms.

Third, AI gives rise to technological innovation. AI is not only about supplementing and replacing manpower with machines. It also promotes the construction of an innovation ecosystem, the formation of corresponding R&D innovation, digestion, absorption and reinvention capabilities, and the true promotion of productivity with the introduction and transformation of intelligent technologies and equipment as a carrier (Li et al., 2020). In this context, Yang et al. (2020) found a significant role of the implementation of AI in promoting the innovation performance of China's manufacturing enterprises. Based on data on industrial robots, Liu et al. (2020) confirmed that AI facilitates technological innovation by accelerating knowledge creation and technology spillover and increasing learning and absorptive capacity as well as R&D and human capital investments. More importantly, AI, especially machine learning, is commonly considered to have the potential to become a "general purpose technology", with such technologies long having been an important driving force in technological progress (Brynjolfsson et al., 2017).

In general, most papers in this field have addressed the role of AI in technological progress. However, as already discussed, energy demand is heightened because of the existence of the rebound effect, resulting in inconsistent conclusions about the effect of technological progress on energy intensity. Machado et al. (2020) theoretically proposed that AI improves productivity and resource efficiency in manufacturing production; examples would include the use of big data for predictive maintenance and rapid reconfiguration of production systems and reductions in waste, energy consumption and overproduction through, for example, sharing of surplus renewable energy with other factories. Using a consensus-based expert elicitation process, Vinuesa et al. (2020) analyzed the positive and negative effects of AI on the Sustainable Development Goals and confirmed that it may potentially benefit the clean energy goals but may undermine the climate goals due to the high need for energy, especially when non-carbon-neutral energy sources are used. However, there is still a lack of empirical research on the impact of AI on energy intensity and on the transmission channel, especially in the case of China, and this is a subject that deserves the attention of scholars and policymakers.

In light of the abovementioned factors, this paper empirically investigates, for the first time, the effect of AI on energy intensity based on data from 2006 to 2016 on industrial robots installed in 16 Chinese industrial subsectors and further discusses the effects of AI on economic output value and energy consumption, the nonlinear impact of AI across different energy intensity groups, and industry heterogeneity in these effects. Finally, taking technological progress as a mediator variable, we examine the transmission channel through which AI exerts its effect on energy intensity.

3. Methodology and Data

3.1. Empirical model

Referring to existing research and considering the availability of data, we use FDI (Huang et al., 2017), ownership status (state or other ownership type) (Luan et al., 2020), enterprise scale (Lin et al., 2018), capital intensity (Bu et al., 2019) and R&D level (Huang et al., 2017) as control variables in our investigation of the effect of AI on energy intensity. Industrial energy intensity can thus be formulated as follows:

$$EI_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 FDI_{it} + \alpha_3 State_{it} + \alpha_4 Scale_{it} + \alpha_5 Capital_{it} + \alpha_6 R\&D_{it} + \varepsilon_{it} \tag{1}$$

where i and t indicate the sector and year, respectively, *EI* represents energy intensity, *AI* indicates the level of AI application, *FDI*, *Stata*, *Scale*, *Capital* and *R&D* represent FDI, share of state-owned enterprises, enterprise scale, capital intensity and R&D level, respectively, α_1 to α_6 denote the marginal contributions of the six variables to be estimated, with α_1, the coefficient of the core explanatory variable *AI*, indicating whether AI enables or inhibits energy intensity reductions, and ε is the error term.

In general, commonly used estimation methods for panel data are the OLS, FE and RE methods. However, in this case, the variables may be autocorrelated, and the fact that the panel data cover several subsectors with different sizes and characteristics naturally induces heteroskedasticity (Zheng et al., 2011), which has great impact on parameter estimation in the OLS, FE and RE methods. In light of this, following Zheng et al. (2011) and Huang et al. (2017), the FGLS method is used in the benchmark regression, and the OLS, FE, and RE approaches are employed in the robustness checks.

3.2. Measurement of energy intensity

Energy intensity is defined as the total energy consumption in the production of one unit of output value. However, the *China Industry Statistical Yearbook* has not provided data on industry output value or added value since 2012. Considering data availability, following Montalbano and Nenci (2019) and Alam et al. (2019), this paper selects industry sales value to substitute for industry output value or added value and uses the ratio of energy consumption to industry sales value to measure energy intensity[1]. We use the industry deflator to adjust the sales values to real 2006 prices. At the same time, to match the IFR industry classification standard and China's industrial classification for national economic activities, we divide the overall industrial sector into 16 subsectors. These data can be obtained from the *China Energy Statistical Yearbook* and the *China Industry Statistical Yearbook.*

3.3. Measurement of AI

In general, AI includes a series of technologies such as machine learning, deep learning, natural language processing, robots, and other technologies. (Cockburn et al., 2018). However, due to the immateriality of machine learning, deep learning and natural language processing, existing studies commonly use industrial robots as a proxy for AI, possibly owing to robots' physical properties, which makes them easier to track over time and space (Acemoglu and Restrepo, 2020b; Liu et al., 2020, 2021). Moreover, this paper focuses on the industrial sector, in which the level of AI application may be better reflected by the number of industrial robots than in other sectors (McElheran, 2018). Therefore, we use the number of industrial robots installed in China's industrial subsectors, as indicated by data provided by the IFR, to measure the AI levels of the subsectors. The more industrial robots a subsector is equipped with, the higher is the AI level of that subsector.

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[1] Sales values reflect the overall economic value of products and are less affected by factors other than energy-saving activities, such as cost savings through labor cost reduction and reductions in the price of intermediate materials. However, sales values are generally larger downstream in the flow of goods from raw materials to finished goods. In addition, upstream industries are generally more resource- and energy-intensive. Therefore, in general, energy intensity, defined as the total energy consumption in the production of one unit of sales value, tends to be higher at the upstream stage and lower at the downstream stage. To deal with this point, this study applies industry fixed effects.

According to the IFR, China has had the world's largest industrial robot market since 2013. In 2018, China installed 154,032 industrial robot units. Although this represented a 1% reduction compared to the 156,176 units installed in 2017, this number of newly installed robots was still greater than the corresponding figure for all of Europe and the US (130,772 units)[2]. Figure 2 shows the changes in the number of industrial robots installed in China's 16 industrial subsectors during 2006-2016. Over this period, the number of industrial robots equipped in China's 16 industrial subsectors rose significantly from 3,690 units in 2006 to 73,121 units in 2016. Furthermore, industrial robot applications are heterogeneous across the different industrial subsectors. For example, in 2016, the electrical/electronics sector, which had the greatest number of industrial robots, was equipped with 29,979 units, while the electricity, gas, and water supply sector had only 57 industrial robot units.

(Insert Figure 2 about here)

3.4. Control variables

3.4.1. Foreign direct investment (*FDI*)

Technology spillovers from FDI are considered an important channel for improving environmental performance. In contrast to host country enterprises, transnational corporations can transfer advanced technology and management experience to local enterprises through the demonstration effect of FDI (Huang et al., 2018). We use the ratio of FDI to industrial sales value as a control variable in our empirical model. The data can be obtained from the *China Industry Statistical Yearbook*.

3.4.2. Ownership status (*State*)

The features of the internal industrial structure, such as the ownership structure, also have a significant effect on energy intensity. Fisher-Vanden et al. (2006) and Luan et al. (2020) point out that foreign-owned enterprises have superior management experience compared to that of

[2] More details can be found in the report of the IFR (https://www.ifr.org/downloads/press2018/Executive Summary WR 2019 Industrial Robots.pdf).

state-owned enterprises, leading to generally higher energy efficiency in foreign-owned enterprises, and thus, ownership structure reforms in China contribute to decreasing energy intensity. We use the ratio of state capital to paid-up capital to represent state ownership. The relevant data are collected from the *China Industry Statistical Yearbook*.

3.4.3. Enterprise scale (*Scale*)

Firm size is an important factor affecting energy intensity. On the one hand, larger enterprises typically exhibit lower energy intensities than smaller firms due to the advantages in efficiency associated with economy of scale (Alok, 2004; Golder, 2011; Fisher-Vanden et al., 2016; Lin et al., 2018). For instance, Lin et al. (2018) argued that the larger firms are, the more efficient is their use of energy and equipment; the authors found that the energy intensity of China's textile industry decreases by 0.216% with a 1% increase in the enterprise scale. These scale economies are encouraged by the closure of small-scale, polluting plants and the restructuring of enterprises, a phenomenon that is represented in China by the strategy of "grasping the large, letting go of the small" (Fisher-Vanden et al., 2016). In addition, larger firms tend to adopt more energy efficiency measures than smaller ones (Schleich, 2009). Small and medium-sized enterprises (SMEs), especially non-energy-intensive ones, invest less in energy management in their production processes and exhibit lower rates of adoption of energy efficiency measures than do larger firms (Gruber and Brand, 1991; Cagno et al., 2010). The ratio of the industrial sales value to the number of firms is utilized to measure enterprise scale. The relevant data are sourced from the *China Industry Statistical Yearbook*.

3.4.4. Capital intensity (*Capital*)

The energy consumption of an industry may be affected by its capital intensity. On the one hand, high capital intensity commonly indicates greater machinery and equipment requirements, resulting in greater demand for power and higher pollution emissions (Bu et al., 2019). On the other hand, capital-intensive industries may also be energy-intensive, requiring more energy such as feedstock and power for production (Lan et al., 2012). This paper uses the ratio of gross fixed capital to annual average number of employees to measure capital intensity. The data can be obtained from the *China Industry Statistical Yearbook*.

3.4.5. R&D activities (*R&D*)

Fisher-Vanden et al. (2006) held the view that R&D activity is one of the main ways in which technological progress can be accelerated and that it is a crucial driver of energy intensity. Increasing R&D not only helps reduce production costs but also improves energy efficiency (Huang et al., 2017). R&D activities are measured by the number of invention patent applications, collected from the China Stock Market & Accounting Research Database.

3.5. Data management

In this paper, we select 2006-2016 as our sample interval based purely on the availability of data. Variable descriptions, including symbols, definitions and units, are listed in Table A1 in the Appendix. To smooth the data, we transform the variables *EI*, *AI* and *R&D* into logarithmic form. The descriptive statistics, a correlation matrix of the variables and the results of unit root tests are summarized in Table A2 of the Appendix. Table A2 shows that the absolute values of the correlation coefficients between variables are less than 0.4537 and that all the variance inflation factors (VIFs) are smaller than the empirical criterion of 10, indicating that there is no significant multicollinearity among the regression variables used in this paper. In addition, three panel unit root tests show that all the variables are stationary at the 5% level of significance and can be further used for empirical analysis.

4. Empirical results

In this section, we first analyze the impact of AI on energy intensity. The impacts across different conditional energy intensity distributions are then investigated based on the QR method. Furthermore, industry heterogeneity in the responses of energy intensity to AI is also discussed. Finally, we examine the endogeneity issue and re-estimate the impact of AI on energy intensity by introducing an alternative AI measurement to strengthen the reliability of our findings.

4.1 Baseline results

We summarize the baseline results obtained using Eq. (1) in Table 1, where the FGLS regressions (models (5) and (6)) are the primary results and the OLS (models (1) and (2)), FE (model (3)) and RE (model (4)) methods are used for comparison. As shown in Table 1, the coefficients of AI across all specifications are negative and significant, suggesting that incremental applications of AI contribute to decreases in energy intensity. Specifically, according to the results obtained using model (6), which includes all control variables and fixed effects, a decrease of 0.0244% in energy intensity accompanies a 1% increase in the number of industrial robots adopted. At the same time, the magnitude and significance levels of the estimated coefficients in models (1) to (5) are highly similar to those in model (6), indicating that the results are not sensitive to the estimation method. Our findings are plausible and consistent with those of Røpke and Christensen (2012) and Wang and Han (2016), who verify the significant negative impact of ICT on energy intensity. There are two possible reasons for this negative impact. First, the technological progress effect of AI can increase output value; this is confirmed by previous findings that AI promotes productivity and economic growth (Purdy and Daugherty, 2017; Graetz and Michaels, 2018). Second, although the training of AI requires considerable energy (Strubell et al., 2019), AI can also deepen the integration of renewable energy and energy efficiency and support the use of low-carbon energy systems, an effect that is beneficial for containing energy demand (Vinuesa et al., 2020). For instance, machine learning and deep learning in energy informatics can be used to create accurate models that can be used to solve energy problems, including energy distribution, prevention of energy waste and theft, pollution reduction, and other problems, thereby contributing to dynamic and economic management of energy (Heghedus et al., 2018). In terms of improving the energy efficiency of robots, path rerouting, reprogramming of robot motions and the use of energy-efficient equipment can effectively reduce the energy consumption of industrial robots in manufacturing systems (Brossog et al., 2015). For example, by varying robot motion profiles, for instance, to avoid peak torques and to follow the eigenfrequencies of the system, energy gains in the range of 30% to 70% can be achieved (Pastras et al., 2019).

Nevertheless, a decrease in energy intensity is not necessarily evidenced by decreasing energy consumption. Since energy intensity is the energy consumption per unit of output value in the production process, it is also possible for AI to reduce energy intensity by increasing output value while increasing energy demand when the positive effect of AI on output value is greater than its positive impact on energy consumption. To evaluate this conjecture, we decompose energy intensity into output value and energy consumption as the explained variables. Considering the data availability, sales value is used to measure output value (*SALES*), and gross energy consumed in the production process is employed as the metric of energy consumption (*ENERGY*). Moreover, to assess the robustness of our results, we further divide the gross energy consumption into coal consumption (*COAL*), oil consumption (*OIL*), natural gas consumption (*GAS*) and electricity consumption (*ELC*) and regard these as the explained variables. All of these energy intensity components are logarithmically transformed. The data are sourced from the *China Industry Statistical Yearbook* and the *China Energy Statistical Yearbook*. In Table 2, models (1) to (6) are the estimated with ln*SALES*, ln*ENERGY*, ln*COAL*, ln*OIL*, ln*GAS* and ln*ELC*, respectively, as the explained variables.

The results show a significantly positive effect of AI on output value. For every 1% increase in the level of AI, the output value increases by 0.0056%. At the same time, AI has obvious negative effects on energy consumption, including gross energy consumption, coal consumption, oil consumption, natural gas consumption and electricity consumption. The empirical results validate our conjecture that AI applications can significantly reduce energy intensity both by increasing output value and by reducing energy consumption.

The coefficients of the control variables, which are shown in Table 1, also align with our overall expectations. Concretely, energy intensity has significantly negative responses to R&D activities and is obviously and positively impacted by state ownership, enterprise scale and capital intensity. In addition, higher FDI can reduce energy intensity, although its effect may be nonsignificant.

(Insert Tables 1 and 2 about here)

4.2 Heterogeneity in conditional distributions

In section 4.1, we confirmed the significantly negative effect of AI on energy intensity, where the effect of AI is implicitly assumed to be uniform across different conditional distributions of energy intensity. In this section, selecting 9 quantiles (i.e., 0.1, 0.2, …, 0.9), we use the panel QR method to further investigate the impact of AI on different energy intensity levels. This approach can specify the complete conditional distributions of energy intensity across different sectors and years (Nguyen et al., 2020) and thereby provide more useful insights than the previously used OLS, FE, RE and FGLS methods, which can only reveal the relationship between AI and the conditional mean of energy intensity.

The heterogeneous impact of AI across different conditional distributions of energy intensity is summarized in Table A3 in the Appendix; to make the results more intuitive, Figure 3 portrays the evolution of the coefficients across the different quantiles. First, in Table A3 and Figure 3, consistent with the baseline results, the coefficients of AI are negative and obvious across all energy intensity quantiles, indicating that AI application can significantly reduce energy intensity in Chinese industries. Second, by comparing the absolute coefficient values, it is easy to observe that AI has greater effects on reducing energy intensity at high quantiles (i.e., 0.7, 0.8 and 0.9). This result is consistent with the results of Chen et al. (2019), who found that deepening of ICT can promote the "lightweight" production model, especially at high quantiles. Another possible reason for this finding is that sectors with higher energy intensity, e.g., paper manufacturing and iron and steel, face higher energy costs and may be more eager to increase their energy efficiency

(Fisher-Vanden et al., 2016) and thus may prefer cleaner AI technology to decrease energy consumption and intensity.

(Insert Figure 3 about here)

4.3 Industry heterogeneity

Thus far, when discussing the impact of AI on energy intensity, we have assumed that all industrial subsectors are homogeneous; this, however, ignores the heterogeneous impacts of AI across different industries that results from uneven development among industrial subsectors and collection of AI technologies (Executive Office of the President, 2016). Thus, the effect of AI on energy intensity may be sector-dependent. To investigate industry heterogeneity in the responses of energy intensity to AI, referring to Chen et al. (2017), we divide the industrial subsectors into labor-, capital- and technology-intensive industries based on their dependence on specific production elements[3] and further introduce the interaction term ln*AI* and the two dummy variables *Labor* and *Tech* into Eq. (1). To improve the reliability of our conclusions, six energy intensity components (i.e., ln*SALES*, ln*ENERGY*, ln*COAL*, ln*OIL*, ln*GAS* and ln*ELC*) are also taken as the explained variables. The regression results on industry heterogeneity are reported in Table 3.

First, the coefficients of ln*AI* remain negative and significant at the 1% level for all models, consistent with the baseline results shown in Tables 1 and 2. Second, it is noteworthy that the coefficients of ln*AI***labor* and ln*AI***tech* are -0.0718 and -0.0640, respectively, and are significant at the 1% level in model (1), revealing that the energy intensity reduction in the labor-, capital- and technology-intensive sectors benefits from increasing AI penetration, although the impact is marginally lower in capital-intensive sectors. This pattern of results, which is consistent with that in Pieri et al. (2018), suggests that the effect of ICT in improving efficiency varies across industries. Possible reasons for this finding are that on the one hand, more tasks that

[3] According to Chen et al. (2017), labor-intensive sectors include the food and beverage, textiles, wood and furniture, and paper industries, capital-intensive sectors include the mining and quarrying, pharmaceuticals, cosmetics, other chemical products n.e.c., rubber and plastic products (nonautomotive), basic metals, glass, ceramics, stone, mineral products (nonautomotive), and electricity, gas, and water industries, and technology-intensive sectors include the metal products (nonautomotive), industrial machinery, transportation equipment, and electrical/electronics industries as well as all other branches of manufacturing.

require low or medium skill have gradually been automated by more efficient AI in recent years (Acemoglu and Restrepo, 2020b); the enormous differences in productivity between AI and human labor thus cause the impact of AI on energy intensity to be more pronounced in labor-intensive sectors. Moreover, technology-intensive sectors enjoy a competitive edge from R&D-induced frontier movements (Pieri et al., 2018). Owing to their absolute advantages with respect to AI infrastructure and talent, these sectors also have greater technology absorptive capacity, an attribute that can reduce the discrepancy between the technical potential of AI and the actual realization of its benefits (Purdy and Daugherty, 2017). Thus, the effect of AI on energy intensity is much stronger in technology-intensive sectors than in other sectors.

Third, according to the coefficients of the interaction terms in models (2) to (7), similar industry heterogeneity also exists in the effects of AI on output value and energy consumption (including consumption of coal, oil, natural gas and electricity). More specifically, the positive effect of AI on output value is greater in labor- and technology-intensive sectors than in capital-intensive sectors, and the negative response of energy consumption to AI is again more pronounced in the former two types of sectors, although the heterogeneity in the effect of AI on electricity consumption in the technology- and capital-intensive sectors is not significant.

(Insert Table 3 about here)

4.4. Robustness check

4.4.1. Endogeneity test

Theoretically, if there is credible evidence that an increasing AI level can decrease energy intensity, it is reasonable to believe that high energy intensity may, in turn, influence policymaking for AI development. That is, there may be a two-way causal relationship between AI and energy intensity, generating endogeneity issues and thus leading to biased estimations. Therefore, we introduce an instrumental variable (IV) and use the 2SLS model to address endogeneity concerns. Following Acemoglu and Restrepo (2020b), we employ the logarithmic form of the number of industrial robots used in the corresponding industrial subsectors in the US as the IV[4], based mainly on the following two considerations. On the one hand, investments in and applications of AI in the US, which are more advanced than those in China, may intensify the international competition faced by Chinese industries and further improve their AI applications (Acemoglu and Restrepo, 2020b), and thus there is a relationship between the instrumental variable (IV) and the endogenous variable. On the other hand, there are no other plausible channels whereby the AI level in the US may influence China's energy intensity. Thus, the number of industrial robots in the US meets the two requirements of the IV approach: i.e., correlation with the endogenous variable and exogeneity.

The 2SLS regression results are summarized in models (1) and (2) of Table A4 in the Appendix. According to the coefficient of model (1), AI adoption in the US is an important indicator that improves AI penetration in China. According to model (2), AI acts as a negative and significant contributor to energy intensity, consistent with the results of the previous analyses. In addition, regarding identification tests, the Anderson canon. corr. LM statistic is significantly greater than the critical value at the 1% level, indicating a rejection of the null hypothesis that the IV is not related to the endogenous variable. The weak identification test rejects the null hypothesis of a weak IV. Moreover, according to the Anderson-Rubin Wald test, the null hypothesis that the sum of the endogenous regression coefficients equals 0 is rejected at the 1% level. The abovementioned three tests show that the IV used in this paper is appropriate.

4.4.2. Controls for selection bias

Considering the relationship between AI and energy intensity mentioned above, it is likely that adoption of AI is a choice or decision variable; i.e., companies or industries that focus on reducing energy intensity are more motivated to choose to apply AI. This means that the application of AI is nonrandom, a condition that generates selection bias. To address this potential bias in the estimates, we use the Heckman two-step approach (Heckman, 1979). Specifically, we include a dummy variable, AI adoption (1 = yes, 0 = no), in the model. In the first step, the dummy variable is used as the explanatory variable, the IV is again the number of

[4] The relevant data are provided by IFR.

industrial robots used in the corresponding US industries, and a probit model is regressed to estimate the probability of an observation entering a sample. In the second step, the selection parameter, the inverse Mills ratio (IMR), is introduced in Eq. (1), and the FGLS model is used to predict the ultimate dependent variable. The regression results are summarized in models (3) and (4) of Table A4 in the Appendix. The results obtained using the Heckman two-step method and those obtained using the baseline are identical, and the signs and significance levels of the regression coefficients obtained using the former method are largely consistent with those in the baseline results.

4.4.3. Alternative AI measurement

To further check the robustness of our findings, we use an alternative AI measure: industrial robot stocks in China's industrial subsectors (Acemoglu and Restrepo, 2020b). In addition to energy intensity, we take ln*SALES*, ln*ENERGY*, ln*COAL*, ln*OIL*, ln*GAS* and ln*ELC* as the explained variables. Overall, the results shown in Table A5 in the Appendix are consistent with the baseline results presented in Tables 1 and 2. For example, expansion of AI can significantly reduce China's industrial energy intensity by both increasing output value and reducing energy consumption. When an alternative AI measure is used, the empirical results of this paper remain robust.

5. Further discussion

5.1. The transmission channel connecting AI to energy intensity

In this section, we further discuss the transmission channel that connects AI to energy intensity. As mentioned above, technological progress has been proven to drive energy intensity and to be affected by AI. Thus, we conjecture that technological progress is the main transmission channel through which AI affects energy intensity. To verify this hypothesis, we adopt the stepwise regression method and the bootstrap method and use technological progress (*TP*) as a mediator variable to test the mediation effect. Following He et al. (2013), we measure technological progress using the Malmquist productivity index[5]. The relevant data can be obtained from the *China Industry Statistical Yearbook* and the *China Energy Statistical Yearbook*.

The results of applying the stepwise regression and bootstrap methods to models (1) to (3) are shown in Table 4. The results for model (1) show that the total size of the effect of AI on energy intensity is -0.0244. Models (2) and (3) demonstrate that the direct component of the effect of AI on energy intensity is -0.0028 (the coefficient of AI in model (3)), while the indirect component of the effect through technological progress is -0.0191 (the coefficient of AI in model (2) multiplied by the coefficient of the mediator variable in model (3)). Thus, the proportion of the total effect accounted for by the mediation effect is approximately 78.3%. In addition, the bootstrap method with 1,000 repeated samplings confirms the obvious mediation effect of technological progress. That is, the application of AI significantly increases technological progress and further reduces energy intensity, validating the hypothesis set forth in this paper.

5.2. Robustness check

To check the robustness of our findings, we retest the transmission channel using industrial robot stocks as an alternative measure of AI in models (4) to (6) and report the results in Table 4. The results confirm the robustness of our conclusions regarding the mediation effect of

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[5] The input variables are net fixed assets, employees (measured as the annual average number of employees) and energy consumption, and the output variable is sales value.

technological progress. In addition, we use the FE model to re-estimate the transmission channel in models (7) to (9) and report the results in Table 4; the results corroborate our previous inference that AI penetration reduces energy intensity by boosting technological progress.

(Insert Table 4 about here)

6. Conclusion and policy implications

In recent years, AI has affected every aspect of our lives, especially the way in which production is organized. However, this increase in AI penetration poses a challenge with respect to energy consumption. Because reducing energy intensity is one of China's most important tasks, a proper evaluation of how AI affects energy intensity is needed. In general, AI penetration in the production process involves technological progress, which in turn influences energy intensity. However, few studies have examined the relationship between AI and energy intensity. Extending the existing literature, we present the first evidence that AI reduces energy intensity, identify industries that are more significantly affected in this way and quantify the mediating role of technological progress in the response of energy intensity to AI. Throughout our study, we analyze the effect of AI on energy intensity, emphasizing that AI contributes to increasing output value and reducing energy consumption and that the higher energy intensity is, the greater is the impact of AI on energy intensity. The effect of AI on energy intensity reduction is more pronounced in labor- and technology-intensive sectors than in capital-intensive sectors. The mediation effect model proves that the impact of AI on energy intensity is primarily achieved through the facilitation of technological progress in that technological progress accounts for 78.3% of the total impact of AI on energy intensity.

This paper not only adds to the new literature on the effect of AI on energy intensity but also has practical implications for green economic transformation. From a policy perspective, first, it is necessary to note the importance of considering the set of effects generated by AI on energy intensity. The government could promote a wave of AI research and AI adoption to incentivize companies to adopt AI to retrofit traditional production equipment and processes, prioritizing the development of sectors in which energy intensity falls within high quantiles and leading to an increase in output value and a decrease in energy intensity. Second, there are significant differences in the effects of AI at different energy intensity levels and in different industries. This suggests that specific adaptive and differentiated policies that address the strengths and characteristics of different sectors should be formulated to enhance the practicality of policy tools.

Our work also has some limitations that could be addressed in the future. First, China has been a relative world leader in the development of AI; this, on the one hand, comes from the support of government, while, on the other hand, many of its enterprises have technical foundations. Therefore, China's companies may gain better productivity effects from implementing AI. It is difficult to guarantee the universality of our conclusion as it applies to other developing countries, and studies conducted in other developing countries are necessary. Second, our paper represents an initial step towards understanding the consequences of AI penetration in Chinese industrial energy consumption. At this stage, the threats of energy shortages and environmental pollution are high-priority concerns to the Chinese government. We hope to make further progress on the impact of AI on energy efficiency and carbon emissions and to provide more microlevel evidence.

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Figures

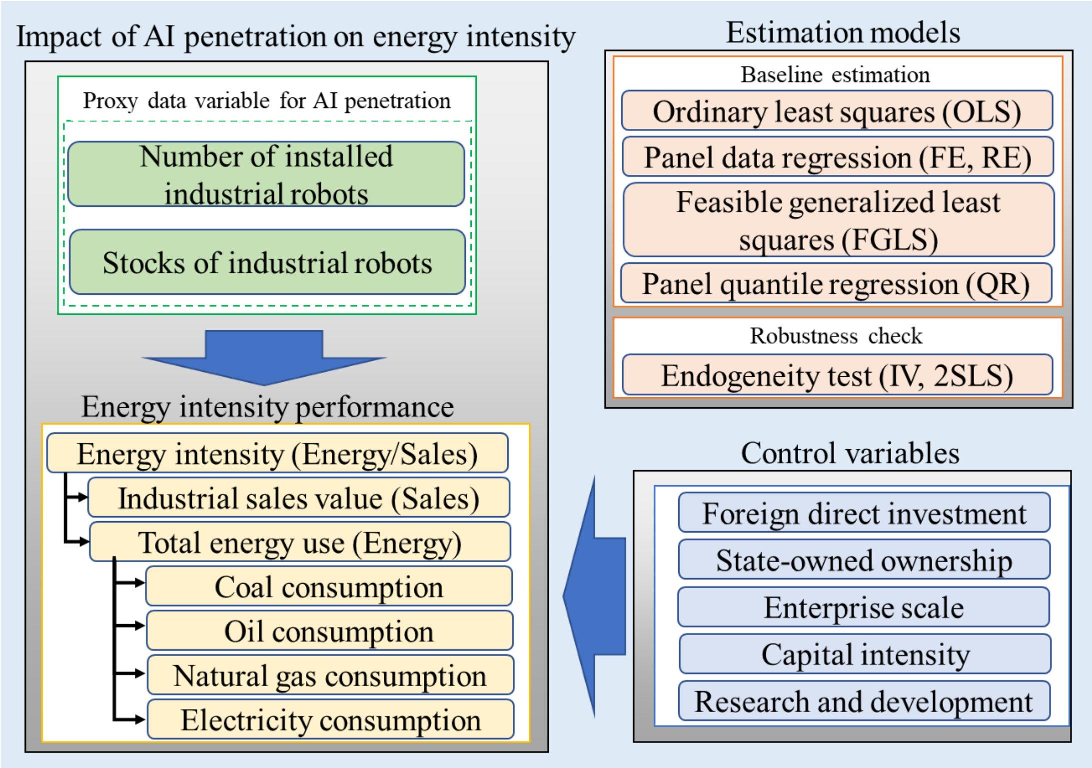

Fig. 1. Research framework of this study.

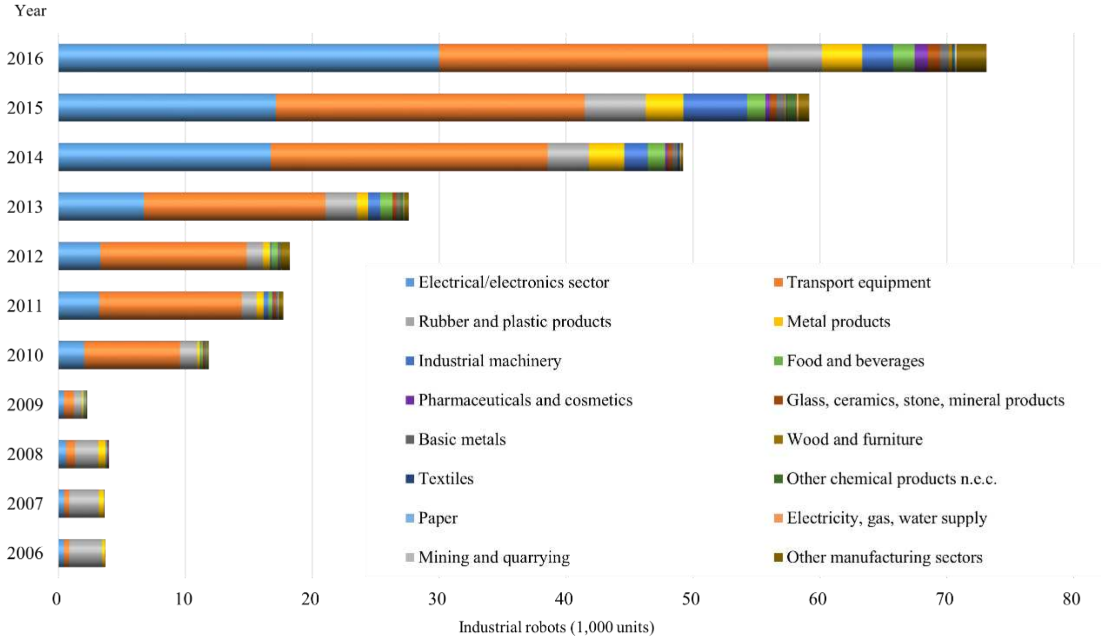

Fig. 2. Changes in the number of industrial robots installed in China's 16 industrial subsectors during 2006-2016. *Source*: International Federation of Robotics (IFR).

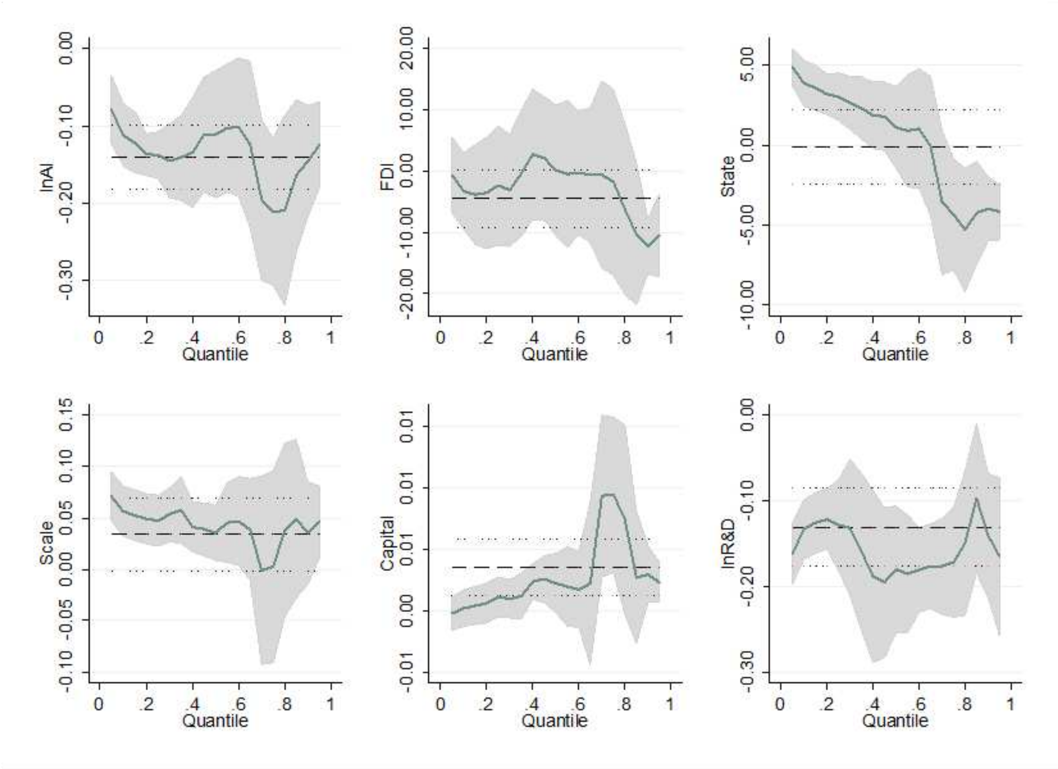

Fig. 3. Evolution of coefficients across different quantiles. *Note*: The dotted line indicates the OLS coefficient at the 95% confidence level, while the solid green line denotes the quantile coefficient. The shaded areas are the areas within the upper and lower limits of the 95% confidence intervals for the quantile regressions.

Tables

Table 1

Baseline estimation (i).

	(1) OLS	(2) OLS	(3) FE	(4) RE	(5) FGLS	(6) FGLS
ln*AI*	-0.1234***	-0.0800***	-0.0177*	-0.0177*	-0.0133***	-0.0244***
	(0.0192)	(0.0185)	(0.0102)	(0.0104)	(0.0024)	(0.0031)
FDI		-11.1233***	-0.0180	0.1725	-0.4144	-0.5019
		(2.0915)	(0.7233)	(0.7382)	(0.3673)	(0.3640)
State		-2.5252**	0.6432	0.9415*	1.8122***	1.5295***
		(1.2464)	(0.5662)	(0.5700)	(0.1406)	(0.3092)
Scale		0.1009***	-0.0889**	-0.0582	0.0156	0.0431**
		(0.0274)	(0.0399)	(0.0385)	(0.0102)	(0.0207)
Capital		0.0266***	0.0076***	0.0074***	0.0055***	0.0077***
		(0.0071)	(0.0016)	(0.0016)	(0.0005)	(0.0011)
ln*R&D*		-0.1054***	-0.3246***	-0.2979***	-0.0777***	-0.1352***
		(0.0279)	(0.0330)	(0.0313)	(0.0091)	(0.0154)
Constant	8.9903***	9.4890***	10.4102***	10.1928***	8.9238***	9.1435***
	(0.0919)	(0.2278)	(0.2258)	(0.2831)	(0.1112)	(0.1042)
Industry fixed effect	NO	NO	YES	YES	YES	YES
Year fixed effect	NO	NO	YES	YES	NO	YES
F-statistic	41.3221	33.7245	10.1449			
Adjusted R-squared	0.1548	0.4599	0.4287			
Wald chi2					797.77	2541.48
Observations	176	176	176	176	176	176

Note: The standard deviations corresponding to the estimated coefficients are shown in parentheses below the individual entries. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 2

Baseline estimation (ii).

	(1)	(2)	(3)	(4)	(5)	(6)
	ln*SALES*	ln*ENERGY*	ln*COAL*	ln*OIL*	ln*GAS*	ln*ELC*
ln*AI*	0.0056***	-0.0176***	-0.0357***	-0.0075	-0.0324***	-0.0096***
	(0.0020)	(0.0029)	(0.0091)	(0.0051)	(0.0100)	(0.0036)
FDI	-4.9256***	-2.3823***	-7.7097***	-1.0926	-6.5560***	-2.8858***
	(0.3321)	(0.5836)	(1.3462)	(1.0308)	(1.1563)	(0.6462)
State	-0.0931	1.7134***	4.6649***	1.4893***	2.4158***	1.7394***
	(0.1744)	(0.1857)	(0.6832)	(0.4846)	(0.7114)	(0.3099)
Size	0.0759***	0.1247***	0.2976***	0.4434***	0.2169***	0.0025
	(0.0068)	(0.0140)	(0.0195)	(0.0534)	(0.0253)	(0.0093)
Capital	0.0016**	0.0058***	0.0187***	0.0057*	0.0163***	0.0050***
	(0.0007)	(0.0011)	(0.0024)	(0.0032)	(0.0027)	(0.0007)
ln*R&D*	0.3100***	0.1414***	0.0876***	0.1586***	0.2206***	0.1273***
	(0.0132)	(0.0103)	(0.0212)	(0.0189)	(0.0172)	(0.0083)
Constant	7.7617***	7.7503***	6.9311***	4.1830***	-0.1402	5.2862***
	(0.0863)	(0.0605)	(0.1285)	(0.1613)	(0.1355)	(0.0453)
Wald chi2	13546.54	6110.71	3584.19	2176.00	16871.74	38451.19
Observations	176	176	176	176	176	176

Note: The standard deviations corresponding to the estimated coefficients are shown in parentheses below the individual entries. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 3

Regression results of industry heterogeneity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln*EI*	ln*SALES*	ln*ENERGY*	ln*COAL*	ln*OIL*	ln*GAS*	ln*ELC*
ln*AI*	-0.0523***	0.0038**	-0.0218***	-0.0394***	-0.0104	-0.0481***	-0.0164***
	(0.0042)	(0.0015)	(0.0038)	(0.0107)	(0.0069)	(0.0055)	(0.0036)
ln*AI*labor*	-0.0718***	0.0066*	-0.0383***	-0.0213	-0.0247**	-0.0536***	-0.0183**
	(0.0063)	(0.0037)	(0.0041)	(0.0381)	(0.0098)	(0.0164)	(0.0086)
ln*AI*tech*	-0.0640***	0.0040*	-0.0290***	-0.1165***	-0.0068	-0.0323***	-0.0029
	(0.0037)	(0.0022)	(0.0046)	(0.0130)	(0.0120)	(0.0079)	(0.0040)
FDI	-2.1130***	-4.8159***	-4.9657***	-6.4468***	-1.5371	-6.3288***	-4.9184***
	(0.6122)	(0.2475)	(0.6873)	(1.5447)	(1.1663)	(0.9749)	(1.0142)
State	1.5513***	-0.2005	1.6556***	5.8185***	1.1320	2.8425***	2.3921***
	(0.2943)	(0.1795)	(0.3365)	(0.5947)	(0.7319)	(0.6920)	(0.3932)
Scale	0.0668***	0.0761***	0.1160***	0.2988***	0.4634***	0.2344***	-0.0183
	(0.0105)	(0.0048)	(0.0181)	(0.0277)	(0.0600)	(0.0144)	(0.0143)
Capital	0.0092***	0.0026***	0.0076***	0.0154***	0.0058	0.0144***	0.0076***
	(0.0011)	(0.0006)	(0.0011)	(0.0026)	(0.0039)	(0.0017)	(0.0015)
ln*R&D*	-0.1302***	0.3027***	0.1694***	0.0839***	0.1613***	0.2314***	0.1674***
	(0.0096)	(0.0118)	(0.0095)	(0.0237)	(0.0197)	(0.0187)	(0.0081)
Constant	9.1600***	7.7899***	7.6838***	6.8710***	4.1813***	-0.2004	5.1106***
	(0.0712)	(0.0751)	(0.0514)	(0.1604)	(0.1750)	(0.1417)	(0.0726)
Industry fixed effect	YES	YES	YES	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES	YES	YES	YES
Wald chi2	8025.52	5481.02	2906.85	3293.58	1630.74	21685.29	39085.82
Observations	176	176	176	176	176	176	176

Note: The standard deviations corresponding to the estimated coefficients are shown in parentheses below the individual entries. *** and ** indicate significance at the 1% and 5% levels, respectively.

Table 4

Mediation effect test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln*AI*	-0.0244***	0.1627***	-0.0028*	-0.1922***	0.7822***	-0.0257***	-0.0177*	0.1598	-0.0188**
	(0.0031)	(0.0229)	(0.0015)	(0.0119)	(0.0720)	(0.0027)	(0.0102)	(0.1242)	(0.0091)
TP			-0.1174***			-0.1100***			
			(0.0032)			(0.0054)			
FDI	-0.5019	-4.1051	-0.3777	-2.5334***	3.6542	0.0000	-0.0180	-10.3701	-1.6374**
	(0.3640)	(4.2414)	(0.2588)	(0.9579)	(5.4188)	(0.2705)	(0.7233)	(8.8106)	(0.7007)
State	1.5295***	-10.0015***	0.9842***	2.6298***	-10.9879***	0.7103***	0.6432	-2.9523	0.0962
	(0.3092)	(1.0622)	(0.1121)	(0.3677)	(2.6393)	(0.1775)	(0.5662)	(6.8962)	(0.5041)
Scale	0.0431**	-0.1439**	-0.0005***	0.0425**	-0.2366	-0.0005***	-0.0889**	0.1620	
	(0.0207)	(0.0621)	(0.0000)	(0.0207)	(0.1495)	(0.0001)	(0.0399)	(0.4857)	
Capital	0.0077***	-0.0313***	0.0007**	0.0104***	-0.0442***	0.0003	0.0076***	-0.0610***	0.0045***
	(0.0011)	(0.0060)	(0.0003)	(0.0015)	(0.0096)	(0.0006)	(0.0016)	(0.0195)	(0.0015)
ln*R&D*	-0.1352***	0.8769***	-0.0202***	-0.1305***	0.8447***	-0.0511***	-0.3246***	1.2825***	-0.2791***
	(0.0154)	(0.1035)	(0.0064)	(0.0110)	(0.0974)	(0.0102)	(0.0330)	(0.4014)	(0.0297)
Constant	9.1435***	-0.6691	9.0280***	9.5315***	-2.0332***	9.2521***	10.4102***	-3.1029	10.3254***
	(0.1042)	(0.6077)	(0.0461)	(0.0753)	(0.7834)	(0.0616)	(0.2258)	(2.7503)	(0.1879)
Industry fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bootstrap mediation effect test		-0.1706***			-0.3126***			-0.3126***	
Wald chi2	2541.48	2324.03	12693.11	1803.02	4262.69	3614.17			
Adjusted R-squared							0.4287	0.4791	0.5604
Observations	176	176	176	176	176	176	176	176	176

Note: The standard deviations corresponding to the estimated coefficients are shown in parentheses below the individual entries. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Appendix

Table A1

Description of variables.

	Definition	Unit
EI	Energy consumption divided by industrial sales value	Tons of coal equivalent / 10^4 RMB
AI	Application volume of industrial robots	1 unit
FDI	FDI amount divided by industrial sales value	%
State	State capital divided by paid-up capital	%
Scale	Industrial sales value divided by number of firms	10^4 RMB / 1 firm
Capital	Net fixed capital divided by annual average size of the employed population	10^4 RMB / 1 person
R&D	Number of invention patent applications	1 unit

Table A2

Descriptive statistics, correlation matrix of variables and unit root tests.

	ln*EI*	ln*AI*	*FDI*	*State*	*Scale*	*Factor*	ln*R&D*
			Panel A: Descriptive statistics				
Mean	8.4675	4.2347	0.0292	0.0408	1.4787	14.1766	7.4165
Std. Dev.	0.9347	3.0253	0.0236	0.0652	1.6767	14.9536	2.4824
Min	6.5612	0	0.0016	0.0003	0.3471	2.6576	0
Max	10.0188	10.1632	0.1015	0.359	8.9577	87.9483	11.4927
Observations	176	176	176	176	176	176	176
			Panel B: Correlation matrix of variables				
ln*EI*	1.0000						
ln*AI*	-0.3996	1.0000					
FDI	-0.3637	0.1030	1.0000				
State	0.3817	-0.3271	-0.3148	1.0000			
Scale	0.3143	-0.0071	-0.0744	0.2995	1.0000		
Capital	0.4537	-0.1572	-0.2502	0.7611	0.4059	1.0000	
ln*R&D*	-0.3211	0.3617	-0.0309	-0.0212	0.0340	0.0797	1.0000
VIFs	/	1.32	1.11	2.75	1.20	2.66	1.18
			Panel C: Unit root tests				
ADF	135.65^{***}	108.06^{***}	99.38^{***}	149.55^{***}	75.11^{***}	131.92^{***}	83.30^{***}
PP	50.58^{**}	77.51^{***}	44.77^{**}	147.41^{***}	44.20^{*}	54.96^{***}	59.07^{***}
LLC	-3.16^{***}	-2.93^{***}	-3.76^{***}	-9.41^{***}	-4.64^{***}	-5.60^{***}	-8.00^{***}

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. ADF, PP and LLC denote the panel Augmented Dickey-Fuller, the Phillips-Perron and the Levin Lin-Chu tests for stationarity, respectively.

Table A3

Quantile regression results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ln*AI*	-0.1117***	-0.1370***	-0.1451***	-0.1341***	-0.1107***	-0.1013**	-0.1957***	-0.2092***	-0.1457***
	(0.0195)	(0.0139)	(0.0225)	(0.0305)	(0.0355)	(0.0451)	(0.0472)	(0.0460)	(0.0296)
FDI	-3.2656	-3.5524	-3.1267	2.7247	0.1615	-0.2970	-0.5858	-6.2283	-12.2549***
	(2.8237)	(2.8067)	(4.2386)	(4.1647)	(4.3316)	(4.9514)	(5.6977)	(6.6357)	(3.2755)
State	3.8540***	3.1726***	2.6417***	1.8608*	1.0884	1.0323	-3.5687	-5.2916***	-3.9733***
	(0.9138)	(0.6207)	(0.7701)	(1.0790)	(1.5647)	(2.1951)	(2.1876)	(1.6896)	(1.0631)
Scale	0.0565***	0.0491***	0.0534**	0.0410*	0.0355	0.0470	-0.0011	0.0382	0.0353
	(0.0124)	(0.0153)	(0.0205)	(0.0242)	(0.0269)	(0.0332)	(0.0426)	(0.0369)	(0.0253)
Capital	0.0002	0.0006	0.0010	0.0024	0.0022	0.0017	0.0093**	0.0074*	0.0030*
	(0.0009)	(0.0008)	(0.0012)	(0.0016)	(0.0023)	(0.0041)	(0.0039)	(0.0038)	(0.0016)
ln*R&D*	-0.1330***	-0.1214***	-0.1312***	-0.1886***	-0.1801***	-0.1806***	-0.1762***	-0.1493***	-0.1402***
	(0.0193)	(0.0228)	(0.0413)	(0.0431)	(0.0354)	(0.0376)	(0.0404)	(0.0458)	(0.0434)
Constant	8.3295***	8.4729***	8.6397***	9.0251***	9.2246***	9.2998***	9.8267***	10.2195***	10.6780***
	(0.1159)	(0.1426)	(0.2710)	(0.3374)	(0.3327)	(0.3567)	(0.3948)	(0.4891)	(0.3523)
Observations	176	176	176	176	176	176	176	176	176

Note: The standard deviations corresponding to the estimated coefficients are shown in parentheses below the individual entries. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table A4

Regression results of the 2SLS model and the Hackman model.

	2SLS		Hackman	
	(1)	(2)	(3)	(4)
	First-stage	Second-stage	First-stage	Second-stage
ln*AI*		-0.1259***		-0.0205***
		(0.0315)		(0.0033)
IV	0.5777***		0.3550***	
	(0.0557)		(0.1370)	
IMR				0.0401***
				(0.0121)
FDI	-0.4453	-11.0392***	-2.7333	-0.3470
	(7.0628)	(2.3080)	(13.1669)	(0.4018)
State	-23.3621***	-3.4214**	-18.8150	0.9827***
	(3.8643)	(1.3998)	(13.0721)	(0.3363)
Scale	-0.1195	0.1061***	0.3964	0.0431**
	(0.1056)	(0.0339)	(0.3490)	(0.0200)
Capital	0.0726***	0.0277***	0.0563	0.0088***
	(0.0179)	(0.0057)	(0.0430)	(0.0012)
ln*R&D*	0.3204***	-0.0863***	0.0913	-0.1432***
	(0.0667)	(0.0248)	(0.1679)	(0.0133)
Constant	-0.9320	9.5530***	-2.9865**	9.1206***
	(0.6206)	(0.1942)	(1.5117)	(0.0904)
Anderson canon. corr. LM statistic		68.41***		
Weak identification test		107.45***		
Anderson-Rubin Wald test		15.73***		
F-statistic		24.9333		
Wald chi2				2058.44
Adjusted R-squared		0.4426		
Observations	176	176	176	176

Note: The standard deviations corresponding to the estimated coefficients are shown in parentheses below the individual entries. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table A5

Alternative measurement of AI: Stocks of industrial robots.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln*EI*	ln*SALES*	ln*ENERGY*	ln*COAL*	ln*OIL*	ln*GAS*	ln*ELC*
ln*AI*	-0.0394***	0.0107***	-0.0186**	-0.0814***	-0.0239***	-0.0868***	-0.0224***
	(0.0051)	(0.0030)	(0.0074)	(0.0129)	(0.0086)	(0.0102)	(0.0047)
FDI	1.7381***	-5.0723***	-1.9232***	-2.5429***	-1.9445*	-4.9482***	-2.2178***
	(0.4656)	(0.2322)	(0.5422)	(0.8881)	(1.0509)	(1.2217)	(0.6568)
State	1.9065***	-0.1666	1.4112***	4.3415***	1.5266***	2.7485***	1.5255***
	(0.2264)	(0.1441)	(0.3061)	(0.6596)	(0.5476)	(0.5978)	(0.3489)
Scale	0.0125	0.0792***	0.1080***	0.2361***	0.3907***	0.2263***	0.0047
	(0.0127)	(0.0056)	(0.0188)	(0.0303)	(0.0490)	(0.0239)	(0.0110)
Capital	0.0039***	0.0018**	0.0035***	0.0106***	0.0058**	0.0128***	0.0051***
	(0.0011)	(0.0007)	(0.0011)	(0.0020)	(0.0026)	(0.0020)	(0.0010)
ln*R&D*	-0.1164***	0.3132***	0.1079***	0.0807***	0.1520***	0.2286***	0.1299***
	(0.0224)	(0.0109)	(0.0141)	(0.0238)	(0.0195)	(0.0174)	(0.0084)
Constant	9.0116***	7.7398***	7.9884***	7.0355***	4.3477***	-0.1440	5.2581***
	(0.1290)	(0.0660)	(0.0885)	(0.1576)	(0.1580)	(0.1439)	(0.0442)
Industry fixed effect	YES	YES	YES	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES	YES	YES	YES
Wald chi2	3259.61	8943.67	15051.17	1495.98	2195.23	4673.20	33854.73
Observations	176	176	176	176	176	176	176

Note: The standard deviations corresponding to the estimated coefficients are shown in parentheses below the individual entries. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.