AI and Carbon Emission: Evidence from a Quasi-natural Experiment in China

Abstract

About one-third of the world's carbon dioxide (CO2) emissions come from China, which is the biggest energy consumer and carbon emitter in the world. This study investigates the effects of China's Artificial Intelligence Innovation Development (AIID) pilots on carbon emission reduction and is considered a quasi-natural experiment. To increase the internal validity of the findings, I assess how China's pilots have reduced carbon emissions using an entropy balancing staggered difference-in-differences model approach. In order to compensate for the limitations of conventional DID models, this paper also employs machine learning techniques (such as random forests, gradient boosting trees, etc.) that are capable of handling high-dimensional data and intricate nonlinear interactions. The results demonstrate that the carbon emissions intensity has significantly decreased as a result of the AIID trials. Further investigation shows that enterprises with varying levels of industry concentration, factor endowment structure, industry carbon consumption, enterprise size, and property rights exhibit heterogeneity in reducing carbon emissions. The results indicate that the government should broaden the scope of organizations covered by the AIID pilots in order to fully achieve their potential to reduce emissions.

Keywords: Artificial intelligence innovation development (AIID) pilot, Emissions reduction, Difference-in-differences model, Entropy balancing, Machine learning

1.Introduction

Since China is a major the power consumer and carbon contributor, contributing to roughly one-third of the world's total greenhouse gas emissions (IEA, 2021), and because it is widely believed that climate change poses a risk to sustainable development, the Chinese government committed in November 2014 to reaching peak greenhouse gases by approximately 2030 and reducing the country's carbon intensity, or CO2 greenhouse gases as a proportion of GDP, by 60% to 65% in comparison to the 2005 levels by the same year. It then declared in September 2020 that it would strive to reach zero greenhouse gases by 2060. It goes without saying that developing and putting into effect well-thought-out, sensible policies for reducing carbon emissions is essential to achieving these greenhouse gas reductions and neutrality targets (Zhang et al., 2022).

Since 2016, China has entered the 3.0 era of digitalization of cities. With the introduction of the "New Generation Artificial Intelligence Development Plan" in 2017, it marks that the development of artificial intelligence has gradually been taken seriously as an important national strategy. The release of the "Guidelines for the Construction of National New Generation Artificial Intelligence Innovation Development Pilot Zones" in 2019 shows that China has begun to rely on local governments to carry out artificial intelligence policy experiments to promote the implementation of artificial intelligence. In the innovative development of the new generation of artificial intelligence, in order to create a number of representative experiences and enable China's artificial intelligence industry to develop better, China's first pilot zone was established in Beijing in February 2019, with

clear main tasks such as establishing an artificial intelligence innovation system and accelerating the integration and application of artificial intelligence. Subsequently, pilot zones were established in Shanghai, Tianjin and other places. By February 2024, 18 regions have established artificial intelligence innovation development (AIID) pilot zones to build a good ecology for the innovative development of artificial intelligence. In Table 1, I present the list of cities in the AIID pilot.

Table 1 Pilot cities of AIID

Year	Pilot cities
2019	Beijing, Shanghai, Tianjin, Shenzhen, Hangzhou, Hefei, Huzhou
2020	Chongqing, Chengdu, Xi'an, Jinan, Guangzhou, Wuhan
2021	Suzhou, Changsha, Zhengzhou, Shenyang, Harbin

Innovation in science and technology has the potential to bring about changes in the energy sector, economy, and industry. While traditional economic expansion also resulted in excessive use of energy and emissions, which in turn generated environmental degradation, the Industrial Revolution aided in the growth of the economy. Macroenvironmental flaws in industrial development are carbon emissions. Modern technological advances that foster conventional economic growth have been made possible by the rise of intelligent technology (Ahad et al., 2020), which improves human life and productivity while lessening the environmental impact of daily activities (Chatti, Majeed, 2022). The science of artificial intelligence, which is a simulation and broadening of human intelligence, is collectively referred to as artificial intelligence (AI) and includes concepts, techniques, technologies, and application systems. AI encompasses a variety of fields, including machine learning, natural language processing, image recognition, and language recognition (Zhang, Lu, 2021). Carbon emissions are produced by the energy used in businesses' operations and production, and the intensity of these emissions increased with each supply chain stage (Waltersmann et al., 2021). AI is the engine for scientific and industrial transformations and has significantly altered advancements in technology, manufacturing and operations, and even social life (Ding et al., 2023). The purpose of this study is to determine the factors that lead to the success of the AIID pilots in lowering carbon emissions in the manufacturing sector. The research concentrates on the results of these pilots. The information gathered will be useful for expanding AIID pilot programs across the nation. To evaluate the effect of the AIID pilots, we also look at a number of variables, including firm age, leverage ratio, ROA, firm size, firm ownership, ESG score.

A strong foundation for examining the effect of the AIID program on the reduction of carbon emissions is provided by AIID pilots as a quasi-natural experiment and the utilization of Chinese A-share manufacturing companies listed on the Shanghai Stock Exchange and Shenzhen Stock Exchange data. This study tackles potential endogeneity concerns related to policy by utilizing a entropy balancing difference-in-differences model method, hence improving the internal validity of the results. This paper further uses machine learning methods that can handle high-dimensional data and complex nonlinear relationships (such as random forests, gradient boosting trees, etc.) to make up for the shortcomings of traditional DID models.

2.Literature review

2.1. The impact of AIID pilots

The factors that influence CO2 emissions from corporations have captured the interest of governmental and academic authorities. The development of the economy (Destek et al., 2020), the structure of industry (Zhang et al., 2020), global trade (Wang et al., 2022b), regulations concerning the environment (Lin et al., 2023), innovation in green technology (Dong et al.,2022) and others were the main basis for discussing the deeper causes of carbon emissions in the studies that have already been conducted. Previous research has concentrated

on emission trading pilots (Shi et al., 2022), low-carbon city pilots (Huo et al., 2022), and green finance reform (Linzhi et al., 2025) and other pilot programs to investigate avenues for reducing carbon emissions. The body of research on the connection between carbon emissions and technology development policies has gradually grown in recent years. In summary, it primarily addresses the following issues: the big data comprehensive pilot zones policy reduces greenhouse gas emissions by driving data-based formation and optimum industrial structure (Xiahai et al., 2023); the smart city pilot policy can reduce carbon dioxide emissions from manufacturing enterprises in China by 23% by boosting the scope of regulation of the environment and promoting green technological innovation (Fan et al., 2021, Guo et al., 2022). Concerning the impact assessment of AIID pilot, Yujie et al (2024) found that the establishment of the national new generation AIID pilot zone can significantly improve the firm ESG performance. But the existing literature lacks exploration of the relationship between AIID pilot policy and corporate CO2 emissions.

2.2. AI and carbon emission

Prior research on smart manufacturing's low carbon economy confirmed that advancing artificial intelligence (AI) can lower carbon intensity (Liang et al., 2022, Moshood et al., 2021, Zhang et al.,2019). AI is therefore a crucial instrument for reaching zero emissions and carbon reduction and can be used to simultaneously achieve economic growth and reduce environmental pressure (Liu et al., 2022). Artificial Intelligence (AI) has the potential to lower carbon emissions in a number of areas, including information facilities, industrial structures, and green breakthroughs. AI technology, for instance, can be used to coordinate the coupling of electricity and carbon in the field of electricity (Chen et al., 2021). By streamlining procedures and enhancing care models, artificial intelligence (AI) in the medical sector can lower carbon emissions (Bloomfield et al., 2021). Industry uses the most energy, making up over 70% of China's total energy use.(Liu et al.,2021) Ensuring sustainability requires low carbon advancements (Gu et al., 2023). Low carbon development can be achieved by utilizing AI technology to increase energy efficiency and decrease resource waste (Chen et al., 2021). Furthermore, by lowering carbon emissions, AI technologies give conventional supply chains greater chances to convert into sustainable supply chains (Wu, Zuo, 2023). Scholars, however, disagree on this point of view. First, as AI has developed, energy costs have decreased, which has encouraged businesses to increase resource extraction, manufacturing, and consumption. This has increased energy consumption and produced a "rebound effect" (Dauvergne, 2022). Second, more data management assistance is needed when the intelligent transformation procedure is not stable enough, which raises energy costs and greenhouse gases (Vinuesa et al., 2020).

2.3. Double machine learning for causal inference

Double machine learning was formally proposed in 2018 (Chernozhukov et al., 2018). Currently, there are two main types of related literature. The first type of literature evaluates the causal relationship in economic phenomena based on double machine learning. For example, Yang et al. (2020) used double machine learning based on the gradient boosting algorithm to explore the average effect of top-ranked audit firms and verified its robustness compared with the propensity score matching method. Zhang et al. (2022) used the night subway service launched in London in 2016 as the background to quantify the impact of the night subway service on London's night economy, housing prices, traffic accidents and crime through double machine learning. Farbmacher et al. (2022) used a national youth longitudinal health survey conducted by the U.S. Bureau of Labor Statistics as a basis, combined double machine learning with causal mediation effect analysis, measured the causal impact of health insurance coverage on youth health levels, and examined the indirect mechanism of regular physical examinations. The second category of literature innovates methodological theories based on double machine learning. For example, Chiang et al. (2022) proposed an improved multi-directional cross-fitting double machine learning estimation method, which not only estimates the robust standard error of double clustering, but also obtains high-dimensional parameter regression results, which can effectively adapt to multi-directional clustering sampling data and improve the effectiveness of the estimation results. Bodory et

al. (2022) combined dynamic analysis with double machine learning to measure the causal effects of multiple treatment variables in different periods, and used weighted estimation to evaluate the dynamic treatment effects of specific sub-samples, enriching the dynamic quantitative extension of double machine learning.

3.Methodology and data

Participating enterprises' production and business decisions may change as a result of the AIID pilot program (Huake et al., 2024), offering a great chance to observe how they behave in lowering emissions through a quasi-natural experiment. Based on data from the Shanghai Stock Exchange and Shenzhen Stock Exchange for Chinese A-share manufacturing companies from 2015 to 2022, this study classifies companies that operate in 18 AIID-participating cities as the treatment group and uses companies in the other provinces and cities as the control group. The firms in the treatment group are then matched with those in the control group using the entropy balancing method. This paper further uses machine learning methods that can handle high-dimensional data and complex nonlinear relationships (such as random forests, gradient boosting trees, etc.) to make up for the shortcomings of traditional DID models.

3.1. Model

Since the AIID is not deployed in all cities at the same time, the effect of the AIID pilot on Chinese firms' reduction of carbon emissions is investigated using a staggered DID model. The model captures the effect of AIID adoption on enterprises' decrease of carbon emissions by taking into consideration distinctions between the control group and the treatment group. The structure of the staggered DID model is as follows.

$$y_{ijt} = \beta_0 + \beta_1 \cdot \text{post}_{it} \cdot \text{treat}_i + \gamma X_{it} + \epsilon_j + \text{year}_t + \mu_{ijt} \tag{1}$$

Where i, j, t represent firms, provinces, and years. y represents a firm's carbon emissions intensity. $treat_i$=0 denotes the control group, $treat_i$=1 denotes the treatment group. $Post_{it} = 1$ denotes that the city where $firm_i$ is situated has been officially given the AIID in $year_t$; $post_{it} = 0$ denotes the exact opposite. The coefficient that highlights the gap in greenhouse gas emissions intensity between the firms included by the AIID and other enterprises before and after the AIID was established is called $\beta 1$. X_{it} is a collection of control variables at the business level that includes firm age, leverage ratio, ROA, firm size, firm ownership, ESG score. The fixed impacts of province and year are denoted by ϵ_j, and $year_t$, respectively. The error term is denoted by μ_{ijt}.

It may be challenging to detect changes in the carbon emissions intensity of firms in program-covered regions before and after the program's implementation because the government did not use a system of randomization for the AIID pilots, which could lead to sample selection bias (Rosenbaum, Rubin, 1983). In order to tackle this problem, I employed the entropy balancing (EB) technique to determine a collection of group of control samples that share the most traits with the groups that were treated. The PSM approach still has a number of shortcomings even though it can somewhat mitigate estimation bias. First, sample loss occurs when samples that do not match successfully are dropped. Secondly, the distribution parameters (i.e., mean, variance, and skewness) of the treatment group's and the control group's chosen control variables could differ. Third, the PSM method's implementation is largely dependent on a few arbitrary choices (Hainmueller, 2012). For instance, researchers nearly usually use a straightforward logit model to compute the propensity score or manually alternate between the weighting allocation and balance checks until the optimal balancing solution is found in order to address the problem of misspecification. Although balance between treatment and control groups is the goal of both the PSM and EB approaches, there are differences in how the control group will be given weight. To put it briefly, the EB approach guarantees that the distribution moments of each regressor's higher-order moments are identical between the two groups as compared to the PSM method (McMullin, Schonberger, 2020). In particular, there were 8169 samples , 3309 in the treatment group and 4860 in the control group. Table 2 displays the descriptive statistics for the variables. The treatment and control groups' weighted means for each

covariate are equalized. I start by putting the EB technique into practice using a panel data model. The EB outcomes for samples treated in 2019 are shown in the Table 3.

Table 2 Descriptive statistics for key variables

	Treatment group				Control group			
	Obs	Mean	SD	Median	Obs	Mean	SD	Median
lnco2intensity	3309	-17.65	1.609	-17.88476	4860	-16.92	1.697	-16.91669
ROA	3309	0.06	0.054	.049831	4860	0.06	0.059	.0468085
Ownership	3309	0.32	0.466	0	4860	0.33	0.469	0
ESG score	3309	4.23	1.017	4.25	4860	4.17	1.049	4
Firm age	3309	8.78	7.738	7	4860	9.90	7.665	8
Leverage ratio	3309	1.40	4.217	1.042079	4860	1.61	4.991	1.091777
Size	3309	22.30	1.523	21.96577	4860	22.25	1.234	22.08169

Machine learning methods, especially those that can handle high-dimensional data and complex nonlinear relationships (such as random forests, gradient boosting trees, etc.), can provide more in-depth analysis compared to entropy balance. Machine learning models can be used to explore the complex relationship between covariates and outcome variables, helping to identify potential interaction effects or nonlinear effects. In order to make up for the shortcomings of the traditional DID model, many scholars have begun to pay attention to the application of machine learning in the field of causal inference (Chernozhukov et al., 2018, Athey et al., 2019, Knittel, Stolper, 2021), and double machine learning is a typical representative of them.

When dealing with high-dimensional control variables, traditional regression models may face the "curse of dimensionality" and multicollinearity, and the accuracy of the estimator is questionable. Double machine learning uses many machine learning and regularization algorithms to automatically screen in the pre-selected high-dimensional control variable set to obtain an effective control variable set with high prediction accuracy, which not only avoids the "curse of dimensionality" caused by redundant control variables, but also alleviates the problem of biased estimation caused by limited main control variables. On the other hand, in economic transformation and growth, nonlinear relationships between variables are the norm. Conventional linear regression may lead to model setting bias and the estimation is not robust enough. However, double machine learning can effectively avoid the model mis-setting problem by virtue of the advantages of machine learning algorithms in processing nonlinear data (Yang et al., 2020). In addition, based on the ideas of instrumental variable function, two-stage prediction residual regression and sample split fitting, double machine learning can alleviate the regularization bias in machine learning estimation and ensure the unbiasedness and effectiveness of the treatment coefficient estimator under small samples (Ellickson et al., 2022)

Based on this, this paper uses a double machine learning model to evaluate the policy effects of AIID.

First, we build a partially linear double machine learning model as follows

$$Y_{+1} = \theta_0 Event_{it} + g(X_{it}) + U_{it} \tag{2}$$

$$E(U_{it}|Event_{it}, X_{it}) = 0 \tag{3}$$

Where i is city,t is year,Y_{+1} is explained variable, $Event_{it}$ is policy variable, θ_0 is the coefficients that this paper focuses on.X_{it} is high-dimensional control variable set, a machine learning algorithm is needed to estimate the specific form $g'(X_{it})$, $U_{it}$is error term,the conditional mean is 0. I estimate equations (2) and (3)

$$\theta^{'} = (\frac{1}{n}\sum_{i\in I, t\in T} Event_{it}^2)^{-1}\frac{1}{n}\sum_{i\in I, t\in T} Event_{it}(Y_{it+1} - g^{'}(X_{it})) \tag{4}$$

where n is sample size

Table 3 Entropy-balancing results (year = 2019).

	Mean			Variance		
	Pilot	Non-pilot		Pilot	Non-pilot	
		Pre	Post		Pre	Post
ROA (2015)	.06079	.05034	.06077	.002573	.001734	.002572
ROA (2016)	.05478	.05324	.05477	.001581	.001877	.001581
ROA (2017)	.05438	.05949	.05436	.001833	.002252	.001832
ROA (2018)	.05105	.05711	.05103	.001496	.002601	.001495
Ownership (2015)	.3701	.349	.3702	.2347	.2278	.2338
Ownership (2017)	.3701	.349	.3702	.2347	.2278	.2338
Ownership (2018)	.3896	.3546	.3897	.2394	.2295	.2385
ESG score (2015)	4.192	4.159	4.19	.7163	.6804	.7161
ESG score (2016)	4.141	4.075	4.14	.8856	.7611	.8853
ESG score (2017)	4.261	4.133	4.26	.8475	.9028	.8472
ESG score (2018)	4.435	4.238	4.434	.8242	1.097	.8239
Firm age(2015)	9.123	9.928	9.12	44.1	40.67	44.08
Leverage ratio (2015)	1.507	1.96	1.506	7.643	24.61	7.641
Leverage ratio (2016)	1.343	1.334	1.342	2.887	1.362	2.886
Leverage ratio (2017)	1.284	1.295	1.284	.4869	.4662	.4867
Leverage ratio (2018)	1.335	1.389	1.335	.9454	2.535	.946
Size(2015)	22.44	22.08	22.44	3.144	1.331	3.143
Size(2016)	22.64	22.25	22.63	3.038	1.318	3.037
Size(2017)	22.82	22.43	22.81	2.893	1.273	2.892
Size(2018)	22.93	22.56	22.92	2.837	1.251	2.836

The weights must be calculated using samples from before the treatment (before 2019). In order for the treated individuals to use the weights calculated before the treatment exactly, the individuals are matched year by year. Some years are omitted for some variables due to collinearity.

Based on the above estimates, we can further examine the estimation bias:

$$\begin{aligned}\sqrt{n}(\theta_0' - \theta_0) = &\left(\frac{1}{n}\sum_{i\in I,t\in T} Event_{it}^2\right)^{-1} \frac{1}{\sqrt{n}}\sum_{i\in I,t\in T} Event_{it}U_{it} \\ &+ \left(\frac{1}{n}\sum_{i\in I,t\in T} Event_{it}^2\right)^{-1} \frac{1}{\sqrt{n}}\sum_{i\in I,t\in T} Event_{it}\left(g(X_{it}) - g'(X_{it})\right)\end{aligned} \tag{5}$$

where $a = \left(\frac{1}{n}\sum_{i\in I,t\in T} Event_{it}^2\right)^{-1} \frac{1}{\sqrt{n}}\sum_{i\in I,t\in T} Event_{it}U_{it}$,it follows a normal distribution with mean 0, $b = \left(\frac{1}{n}\sum_{i\in I,t\in T} Event_{it}^2\right)^{-1} \frac{1}{\sqrt{n}}\sum_{i\in I,t\in T} Event_{it}\left(g(X_{it}) - g'(X_{it})\right)$, It should be noted that double machine learning uses machine learning and its regularization algorithm to estimate the specific function form $g'(X_{it})$, which inevitably introduces regularization bias. Although it can prevent the variance of the estimator from being too large, it also leads to its lack of unbiasedness, which is specifically manifested in the slow convergence of $g'(X_{it})$ to $g(X_{it})$, $n^{-\phi_g} > n^{-1/2}$,therefore, as n tends to infinity, b also tends to infinity, and θ_0' is difficult to converge to θ_0.

In order to speed up the convergence and make the estimated value of the treatment coefficient satisfy the unbiased property under small samples, the auxiliary regression is constructed as follows

$$Event_{it} = m(X_{it}) + V_{it} \tag{6}$$

$$E(V_{it}|X_{it}) = 0 \tag{7}$$

$m(X_{it})$ is the regression function of the treatment variable on the high-dimensional control variable. It is also necessary to use machine learning algorithms to estimate its specific form $m'(X_{it})$, V_{it} is the error term, and the conditional mean is 0

The specific operation process is: first, use the machine learning algorithm to estimate the auxiliary regression $m'(X_{it})$ and take its residual $V_{it}' = Event_{it} - m'(X_{it})$. Secondly, use the machine learning algorithm to estimate $g'(X_{it})$ and change the main regression form to $Y_{+1} - g'(X_{it}) = \theta_0 Event_{it} + U_{it}$. Finally, use V'_{it} as the instrumental variable of $Event_{it}$ for regression to obtain the unbiased coefficient estimate as follows:

$$\theta_0^{'} = (\frac{1}{n} \sum_{i \in I, t \in T V'_{it}} Event_{it})^{-1} \frac{1}{n} \sum_{i \in I, t \in T V'_{it}} (Y_{+1} - g^{'}(X_{it})) \tag{8}$$

(8) can be approximately expressed as

$$\begin{aligned} \sqrt{n}(\theta_0' - \theta_0) = (E(V_{it}V^2)^{-1} \frac{1}{\sqrt{n}} \sum_{i \in I, t \in T} V_{it}U_{it} \\ + (E(V_{it}V^2)^{-1} \frac{1}{\sqrt{n}} \sum_{i \in I, t \in T} (m(X_{it}) - m'(X_{it}))\,(g(X_{it}) - g'(X_{it})) \end{aligned} \tag{9}$$

$(E(V_{it}V^2))^{-1} \frac{1}{\sqrt{n}} \sum_{i \in I, t \in T} V_{it}U_{it}$ follows a normal distribution with mean 0.Because machine learning is used twice,the convergence speed of $(E(V_{it}V^2))^{-1} \frac{1}{\sqrt{n}} \sum_{i \in I, t \in T} (m(X_{it}) - m'(X_{it}))(g(X_{it})\,(-g'(X_{it}))$ depends on the convergence speed of $m'(X_{it})$ to $m(X_{it})$ and $g'(X_{it})$ to $g(X_{it})$,that is $n^{-(\phi_g + \phi_m)}$,compared to (5),$\sqrt{n}\theta_0^{'} - \theta_0$ converges to 0 faster, thus obtaining an unbiased estimate of the treatment coefficient.

3.2. Data and variables

I use data from 2015 to 2022 from Chinese A-share manufacturing businesses registered on the Shenzhen and Shanghai stock exchanges. Carbon emissions are rarely disclosed by businesses, hence data are not readily available. The carbon emissions intensity of businesses, which is calculated by dividing the total carbon emissions by the year's business revenue, is the dependent variable. This study (Bin et al., 2023) measures the carbon emissions of the industry using the 2006 IPCC National Greenhouse Gas Guides to obtain the standard coal conversion coefficient and the coefficient of carbon emissions, which are based on China's energy annual yearbook by energy consumption. The industry carbon emissions =$\sum$ Each energy consumption * conversion coefficient of standard coal * carbon emission coefficient including eight types of energy : natural gas, kerosene, diesel, gasoline, fuel oil, petroleum, coke, and raw coal. The enterprise's greenhouse gas emissions are then calculated by multiplying the industry's carbon dioxide emissions by the weight of the enterprise's primary business costs occupied by the industry's primary business costs. In this paper, I calculated the log values of the intensity of carbon emissions.

The industrial sector is the exclusive focus of my research, which I have broken down into 16 categories: Mining industry, Food and beverage industry, Textile industry, Wood and furniture industry, Paper, paper products and printing industry, Plastic Chemical Industry, Non-metallic mineral products industry, Basic Metal Industry, Metal products industry, Industrial Machinery Manufacturing, Transportation Equipment Manufacturing, Electronic equipment manufacturing, and Electricity, heat, gas and water production and supply.

Based on prior research and available data, this study adjusts for a number of firm-level factors to more accurately depict the effect of the AIID pilots on lowering carbon emissions. Firm age, leverage ratio, ROA, firm size, firm ownership, and ESG score are the six variables that make up the control variables. The leverage

ratio is calculated by dividing the total liabilities by the total assets, and the firm age is the amount of years since the company was founded. The logarithm of the firm's total assets is used to calculate its size, and ROA is the ratio of net earnings to total assets. ESG is a company's average ESG score. For state-owned enterprises (SOEs), company ownership is represented by a dummy variable that has a value of 1 for SOEs and 0 otherwise.

The following procedures were used in this study to lessen the impact of extraneous variables and guarantee the validity and correctness of the data: (1) leaving out delisted companies, *ST (special treatment*, which refers to listed businesses with losses for three consecutive fiscal years with withdrawing cautionary statements), PT (special transfer, which refers to the stopping of any trading and waiting for the delisting of the listed companies) (2) The research winsorized every continuous variable at the 1% and 99% levels in order to remove the impact of extreme values.

4.Results and discussion

This section looks at how the carbon emissions intensity changed between two groups of firms: the control group, which was not covered by the AIID pilots, and the treatment group. In order to verify the accuracy of the findings from the AIID pilots, I additionally investigate possible heterogeneity and perform a number of robustness tests.

4.1. Baseline results using entropy balance

Table 4 reports the estimated results of the baseline regression model. In column (1), no fixed effects are controlled for, no control variables are included, and the standard errors are not adjusted for clustering. Control variables are added to the model in columns (2). Column (3) and (4) further considers firm characteristics variables while also controlling for fixed effects of year and province. Finally, in column (5) the standard errors are adjusted for clustering at the firm level. The results show that the estimated coefficients in columns (1) to (5) are significantly negative. This shows that the carbon dioxide intensity of enterprises in the treatment group, as opposed to those in the group used as a control, has significantly decreased as a result of the introduction of the AIID programs in 18 cities, the decrease ranged from 0.23 to 0.55.

Table 4 Results of benchmark regression.

	(1)	(2)	(3)	(4)	(5)	(6)
	Co2int	Co2int	Co2int	Co2int	Co2int	Co2int
Staggerdid	-0.227***	-0.340***	-0.549***	-0.418***	-0.418**	-0.403***
	(-3.42)	(-5.89)	(-8.13)	(-5.66)	(-2.18)	(-6.72)
Control variables	-	YES	YES	YES	YES	YES
Year FE	-	-	YES	YES	YES	YES
Province FE	-	-	-	YES	YES	YES
Cluster SE	-	-	-	-	YES	YES
N	4088	4088	4088	4088	4088	8169
R^2	0.003	0.286	0.295	0.347	0.347	-
Adj. R^2	0.00	0.28	0.29	0.34	0.34	-

Notes: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. I cluster standard errors at the firm level when indicated.

4.2. Tests for heterogeneous treatment effects

The typical two-way fixed effect model's regression results will be skewed by the heterogeneity of treatment effects in unit and time dimensions that emerges from the staggered DID approach (Chaisemartin et al., 2020. Callaway, Sant'Anna, 2021). The "bad control group" issue in the TWFE system is that samples that get treatment earlier will become a control group of samples that get treatment later due to the distinct treatment

time points, which could cause estimation bias, as noted by Goodman-Bacon (2021). Furthermore, the calculated coefficients of every time period will become difficult to evaluate due to cross-contamination across periods.

In order to address recent concerns regarding the quantity of TWFE estimates for staggered DD, this paper conducts an event study to test parallel trends and discover alterations in carbon emissions intensity prior to and after the program application across various time periods using Gardner's (2022) two-stage differences in differences model (DID2S). By comparing the differences in results between the two groups, the second stage of

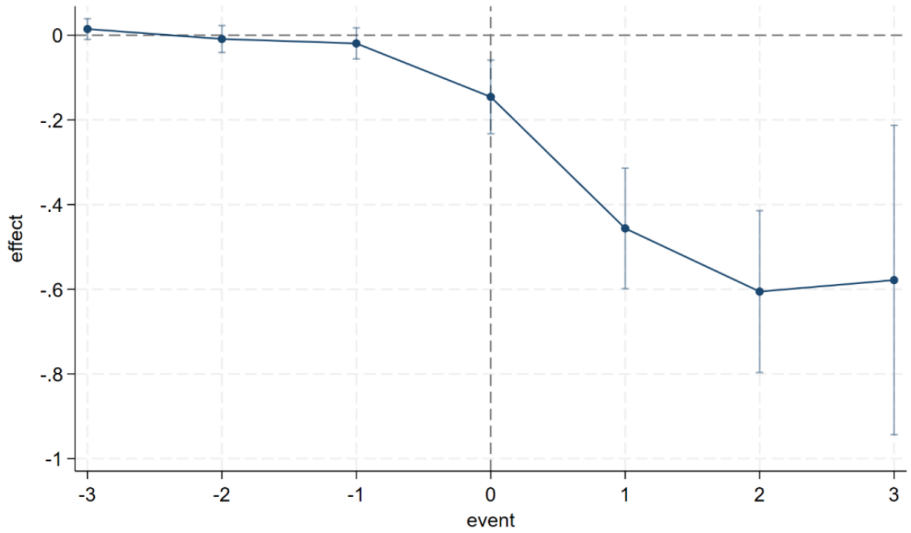


Figure 1 Parallel trend test of the AIID pilots. Notes: Figure 1 shows the change in carbon emissions intensity of firms before and after the implementation of the AIID pilots. The horizontal coordinates are the time from the policy shock, and the vertical coordinates are the estimated coefficients. The middle point in each vertical line of the horizontal coordinate is the parameter estimate, and the two endpoints are the confidence intervals at the 95% confidence level.

this paradigm determines the average effect of treatment after group and period effects have been eliminated. When the treatment impact is diverse and the treated period is staggered, the two-stage estimate approach remains robust. The findings utilizing did2s are displayed in Table 4 columns (6). Each specification shows a negative and substantial effect, demonstrating that the estimating method has no bearing on the results. It is important to note that the DID2s method's estimated coefficients are lower than the baseline regression's. The influence of AIID might have been overstated as a result of the TWFE estimation's flaws.

The event study's estimation results are displayed in Figure 1. The three periods prior to and following the AIID's development are the primary subjects of this essay. It demonstrates that the coefficients of regression in the results were not much different from 0 prior to the establishment of an AIID. This finding confirms the parallel trend concept and shows the precise time trend between the treatment and control groups prior to establishing an AIID. All dependent variables' regression coefficients eventually show signs of statistical significance following the establishment of an AIID.

4.3. Baseline results using double machine learning

This paper uses a double machine learning model to estimate the policy effect of AIID on carbon emissions, where the sample split ratio is 1:4. The random forest algorithm is used to predict and solve the regression. The regression results are shown in the Table 5. column (1) controls the province fixed effect, time fixed effect and the first-order term of the control variable, and column (2) further controls the second-order term of the control variable. Columns (3) and (4) use the lasso algorithm, and columns (5) and (6) use the gradient boosting algorithm. The results show that the AIID pilot has a significant negative effect on carbon emissions.

4.4 Robustness test

Table 5 Regression results using double machine learning

	(1)	(2)	(3)	(4)	(5)	(6)
	Random forest algorithm		Lasso algorithm		Gradient boosting algorithm	
Staggerdid	-0.411***	-0.402***	-0.365***	-0.317***	-0.400***	-0.399***
	(-7.76)	(-7.59)	(-7.36)	(-4.32)	(-7.85)	(-7.84)
First-order term of the control variable	YES	YES	YES	YES	YES	YES
Second-order term of the control variable	-	YES	-	YES	-	YES
_cons	-0.012	-0.011	0.002	-0.010	0.000	0.000
	(-0.85)	(-0.84)	(0.14)	(-0.61)	(0.03)	(0.00)
N	8169	8169	8169	8169	8169	8169

Notes: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. I cluster standard errors at the firm level when indicated.

4.4.1 Placebo test

In the benchmark regression, this paper controls the impact of multiple enterprise characteristics on the treatment group and the control group, but unobservable factors at the enterprise-year level may still affect the estimation results. For robustness considerations, we randomly assign policy shocks to enterprises and years to conduct a placebo test, and finally use the pseudo core explanatory variable DID to replace the staggerdid in equation (1) for regression.

Fig.2 displays the estimated coefficients' kernel density distributions along with the associated p-values for each of the 500 treatment groups that were created at random. The p-value is often higher than 0.05, and the mean value of the calculated coefficient of the new post × treat term is near zero. In addition, the vertical line in Figure 2 shows the estimated coefficient of -0.41, which is outside the main distribution. Consequently, the impact of the variables that were omitted does not substantially skew the empirical findings of this investigation.

4.4.2 PSM

I use PSM to balance data, prior to matching, the firm characteristics of the treatment and control groups differed significantly. After matching, nevertheless, the groups did not differ significantly at the 1% significance level. To compare the statistical distributions of the control and intervention groups prior to and following matching, we also made kernel density distribution maps. The findings show that the two groups' density functions after matching are largely comparable, indicating that the PSM approach was successful in balancing the two groups' attributes. Fig. 3 show the kernel density distributions of the samples in the treatment and control groups before and after matching using the PSM method. The regression results presented in column (1) of Table 6, which do not differ significantly from the baseline regression results.

4.4.3 Other robustness test

Another worry was that the quality of company reports might have affected our regression results. If the quality of the data revealed in a company's yearly report is too low, the metric we use to gauge AI penetration may be significantly off. In order to eliminate this potential bias, we re-ran our initial regression after obtaining the disclosure evaluation ratings of every listed company and keeping the sample of businesses with exceptional and good disclosure evaluation ratings. Table 6 column (2) displays the regression results, which are not much different from the previous regression results.

Municipalities directly under the central government, such as Beijing, Shanghai, Tianjin, and Chongqing, as cities directly under the central government, often enjoy higher financial support and policy priorities, and

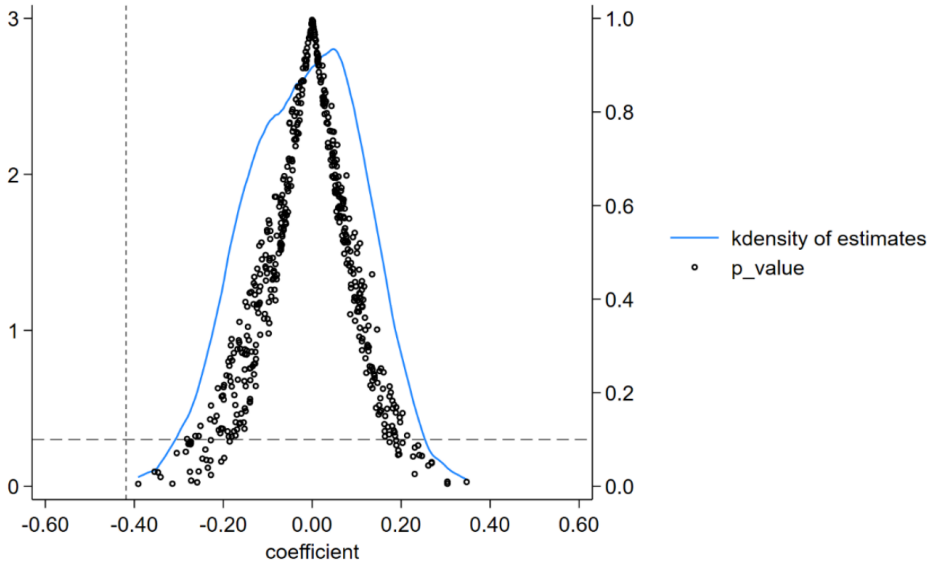


Figure 2 placebo test. Note: The horizontal coordinate represents the estimated coefficients, and the vertical coordinate is the density and P-value. The vertical dashed line denotes the estimated values from the benchmark model.

the intensity and timetable for implementing environmental protection policies may be faster than that of other provinces. This policy advantage may cause the situation in these cities to be unrepresentative, thus affecting the model results. Therefore, column (3) of Table 6 excludes the four municipalities from the sample. The impact of AIID is still significantly negative, indicating that the regression results of this article are sufficiently robust.

Given the potential for a delayed effect of AIID on industrial enterprises' CO2 emissions, we apply a one-period delay to the dependent variable and all control variables. The coefficient of AIID for the first lag period is considerably negative, as seen in Column (4) of Table 6, suggesting that the potential lag of the policy effect has no bearing on the main findings of this work.

China's carbon trading market was launched in 2021, initially covering the power industry, but is expected to gradually expand to other high-emission industries. Carbon emission trading provides companies with economic incentives to reduce carbon emissions to meet set quotas. This policy may interfere with our results, so I excluded samples after 2021 and the power industry, Table 6 Column (5) shows the robust result.

4.5. Heterogeneous effects of AIID

This section mainly studies the heterogeneity impact of industry concentration, factor endowment structure, industry carbon emissions, enterprise scale and property rights on carbon emissions. The specific results are shown in Tables 7 and 8.

4.5.1. Heterogeneity in degree of industry concentration

AI-induced carbon reduction effect is heterogeneously affected by differences in industrial concentration. I separated the sample into two groups—one with a high industry concentration and the other with a low industry concentration—to examine the impact of AIID. Columns (1) and (2) in Table 7 shows that the carbon intensity of high industry concentration firms in the treated group decreased by 0.69 after implementing the AIID. However, the decrease is not observed among the low industry concentration firms in the treated group.

The effect of AIID on carbon emission reduction is more significant in industries with high industry concentration. In highly concentrated industries, the market is dominated by a few large enterprises. These enterprises have stronger capital and technical strength, can afford the high investment in AI technology, and

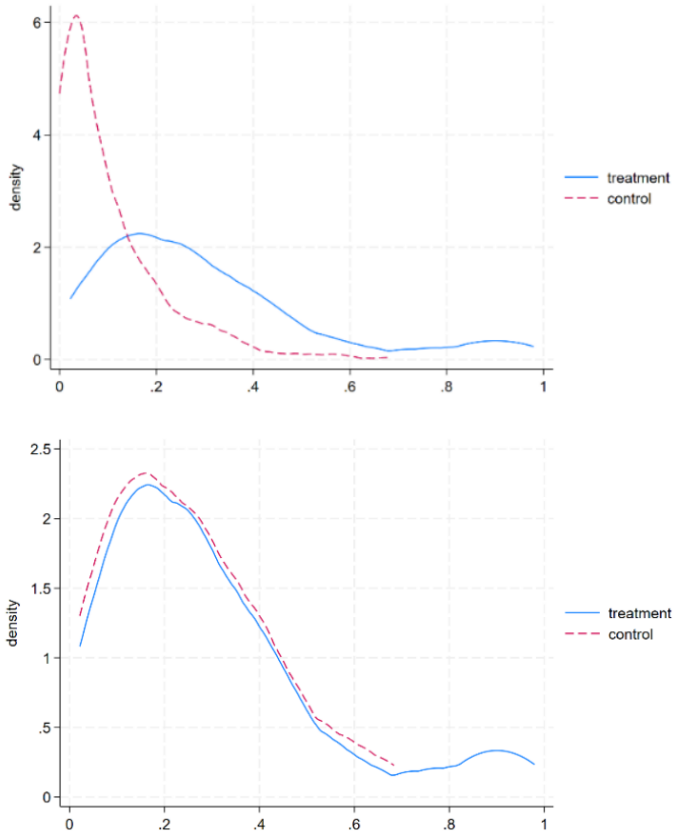


Figure 3 Kernel density distribution of treatment and control groups using PSM. Notes: The horizontal coordinate is the propensity-score and the vertical coordinate indicates the density. Parts (a) and (b) in Figure 3 show the kernel density distributions of the samples in the treatment and control groups before and after matching using the PSM method, respectively.

use economies of scale to reduce marginal costs, thereby more effectively improving energy efficiency and reducing carbon emissions. At the same time, the technology diffusion effect of leading enterprises is stronger. Once AI is first applied to optimize production and carbon management, other enterprises in the industry are also more likely to follow up, forming a wide range of knowledge spillover effects. In addition, highly concentrated industries usually have tighter supply chain integration capabilities, and AI technology plays a more significant role in optimizing resource allocation and reducing energy waste. Moreover, the government often imposes stricter environmental protection supervision on the leading enterprises in these industries, and policy incentives and constraints prompt enterprises to more actively adopt AI technology to achieve carbon emission reduction goals. In addition, market competition pressure also prompts these enterprises to stay ahead in ESG compliance in order to improve market recognition. In contrast, enterprises in low-concentration industries are dispersed, with limited capital and technology investment capabilities, low supply chain coordination efficiency, weak policy impact transmission, and competition relies more on price wars rather than technology upgrades, resulting in limited promotion of AI technology and less significant carbon emission reduction effects than in highly concentrated industries.

4.5.2. Heterogeneous effects of factor endowment structure

AI-induced carbon reduction impacts may also be heterogeneously affected by variations in factor endowment structure. I divided industries into three categories: labor-, capital-, and technology-intensive. I then looked at how AIID affected each of these categories.Columns (3) (4) and (5) in Table 7 represent the regression results for labor-, capital-, and technology-intensive firms, respectively. The coefficient is not significant for labor-intensive

Table 6 Robustness test

	(1) Co2int	(2) Co2int	(3) Co2int	(4) Co2int	(5) Co2int
Staggerdid	-0.250**	-0.436**	-0.535**		-0.405***
	(-2.04)	(-2.20)	(-2.20)		(-2.73)
L.staggerdid				-0.508***	
				(-2.69)	
_cons	-19.350***	-17.796***	-16.742***	-18.350***	-22.498***
	(-15.03)	(-12.40)	(-9.90)	(-13.31)	(-15.72)
N	2559	3178	3415	3441	3175
R^2	0.398	0.329	0.341	0.280	0.667
Adj. R^2	0.39	0.32	0.33	0.27	0.66

Notes: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. I cluster standard errors at the firm level when indicated.

Table 7 Heterogeneous impact of AIID (industry concentration and industry factor endowments)

	Industry concentration		Industry factor endowments		
	(1) High Concentration	(2) Low Concentration	(3) Labor-Intensive	(4) Capital-Intensive	(5) Technology-Intensive
Staggerdid	-0.693***	0.105	0.246*	-0.332***	-0.571***
	(-6.41)	(1.26)	(1.79)	(-2.64)	(-6.84)
Control variables	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES
Cluster SE	YES	YES	YES	YES	YES
R^2	0.386	0.474	0.716	0.589	0.340

Notes: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. I cluster standard errors at the firm level when indicated.

firms, and carbon emissions intensity of capital- intensive firms in the treated group decreases by 0.33, carbon emissions intensity of technology - intensive firms in the treated group decreases by 0.57.

The effect of AIID on carbon emission reduction is most significant in technology-intensive enterprises, but relatively small in capital-intensive enterprises, and not significant in labor-intensive enterprises. Technology-intensive enterprises rely on high-level RD and intelligent production. AI can optimize production processes, improve energy efficiency, reduce material loss, and accurately monitor carbon emissions through data analysis, thereby achieving significant emission reduction effects. In contrast, carbon emissions of capital-intensive enterprises mainly come from energy consumption and industrial processes. Although AI can optimize energy consumption through intelligent scheduling and equipment maintenance, it is limited by the fixed asset renewal cycle and infrastructure constraints, and the carbon emission reduction effect in the short term is relatively small. In labor-intensive enterprises, production relies on manual operations, and carbon emissions mainly come from indirect energy consumption, such as lighting and air conditioning. The application of AI technology is relatively low, and even if management is optimized, its carbon emission reduction effect is still not obvious.

4.5.3 Heterogeneous effects of industry carbon consumption

This paper divides the industries of listed companies into low-carbon and high-carbon sectors and analyzes

Table 8 Heterogeneous impact of AIID (Industry carbon consumption, size and nature of property rights)

	Industry carbon consumption		Size		Nature of property rights	
	(1)	(2)	(3)	(4)	(5)	(6)
	High-carbon industry	Low-carbon industry	Large-size firms	Small-size firms	Non-SOEs	SOEs
Staggerdid	-0.462***	-0.054	-0.234***	-0.791***	-0.671***	-0.107
	(-4.99)	(-0.58)	(-2.79)	(-5.78)	(-7.07)	(-1.01)
Control variables	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
Cluster SE	YES	YES	YES	YES	YES	YES
R^2	0.322	0.524	0.353	0.442	0.294	0.478

Notes: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. I cluster standard errors at the firm level when indicated.

the impact of AIID on their carbon emissions. An industry is considered high-carbon if it contributes more than 2% of total CO2 emissions. The high-carbon sectors include eight industries: non-ferrous metals, power generation, iron and steel, petrochemicals, chemicals, building materials, paper, and aviation. We can see that the impact on high-carbon sectors is greater. Columns (1) and (2) in Table 8 shows that the carbon intensity of high-carbon sector in the treated group decreased by 0.46 after implementing the AIID. However, the decrease is not observed among the low-carbon sector in the treated group.

The effect of AIID on carbon emission reduction is usually more significant in high-carbon enterprises than in low-carbon enterprises. High-carbon enterprises have a high carbon emission intensity, a large proportion of energy consumption in the production process, and many inefficient links, so the marginal emission reduction benefits brought by AI optimization are greater. AI technology can reduce energy waste and improve equipment operation efficiency through intelligent scheduling, accurate prediction of energy demand, and optimization of production processes, thereby producing significant energy-saving and emission reduction effects in high-carbon industries. However, low-carbon enterprises themselves have a small carbon emission base, and the space for AI optimization is relatively limited, resulting in their carbon emission reduction effect not being as obvious as that of high-carbon enterprises. high-carbon enterprises often have more complex production processes and energy management systems. AI can accurately identify carbon emission sources and optimize energy consumption structure through big data analysis and machine learning. For example, in industries such as steel, cement, and petrochemicals, AI can optimize blast furnace operations, reduce excess fuel use, and increase waste heat recovery rates, while these means have limited application value in the production model of low-carbon enterprises. High-carbon industries are usually subject to stricter policy and environmental regulatory pressures, and enterprises need to find effective technical means to reduce carbon emissions in line with policy requirements. As an intelligent energy-saving and emission-reduction tool, AI is more likely to obtain policy incentives and technology promotion in these industries, thereby further strengthening its carbon emission reduction effect. Low-carbon enterprises are under less regulatory pressure on carbon emissions, and have relatively insufficient motivation to adopt AI for carbon management. At the same time, since high-carbon industries have a higher proportion of energy costs, the economic benefits of AI optimizing energy consumption are more obvious, and companies have a stronger desire to invest in AI technology to reduce production costs. However, the proportion of energy consumption in low-carbon enterprises is relatively low, and the savings brought by AI optimization are relatively limited. The return on investment of enterprises in this regard is low, resulting in a relatively weak carbon emission reduction effect.

4.5.4 Heterogeneous effects of enterprise size

This study measures company size using corporate the end of the year total assets to confirm if corporate size has an impact on AIID. The median firm size in the sample is then used in this paper to categorize businesses into large and small businesses.Columns (3) and (4) in Table 8 represent the regression results for large and small firms, respectively. The carbon emissions intensity of large firms in the treated group decreases by 0.23, carbon emissions intensity of small firms in the treated group decreases by 0.79.

The effect of AIID on carbon emission reduction is usually more significant in small enterprises than in large enterprises. Small enterprises usually have lower production efficiency, more traditional energy use methods, and relatively high carbon emission intensity, so the optimization effect brought by AI technology is more obvious. AI can help small enterprises optimize production processes, reduce energy waste, and improve equipment utilization, so that they can obtain greater carbon emission reduction benefits in the short term. For large enterprises, their production processes and management systems are relatively mature, and the optimization space of AI is relatively limited, and the marginal emission reduction effect is relatively small. Secondly, the decision-making and operation models of small enterprises are more flexible. Compared with the lengthy approval processes and complex organizational structures of large enterprises, small enterprises are more likely to quickly adopt and adjust AI technology to adapt to production and energy-saving needs. Large enterprises are often constrained by existing production systems, and the application of AI requires a longer adaptation cycle, resulting in less obvious carbon emission reduction effects in the short term than small enterprises. Small enterprises have a low starting point in technology penetration, and the introduction of AI is equivalent to a technological leap, which rapidly improves energy efficiency and management levels; while large enterprises already have a high level of automation and digitalization foundation, and the marginal improvement effect of AI is relatively weak. Since small businesses have limited resources, AI can help them allocate energy and raw materials more effectively, improve operational efficiency, and reduce unnecessary energy consumption and carbon emissions. Large enterprises usually have sufficient resource reserves, and their energy conservation and emission reduction rely more on long-term equipment upgrades and systematic reforms rather than short-term AI optimization. In terms of environmental supervision, large enterprises usually face stricter compliance requirements and have already taken a variety of emission reduction measures. Small enterprises may lack systematic carbon management methods before the intervention of AI technology. Therefore, the emission reduction effect of AIID on small enterprises is more prominent.

4.5.5. Heterogeneity in the nature of property rights

The effects of carbon reduction may vary depending on the type of property rights that businesses own. I separated businesses into state-owned enterprises (SOEs) and non-SOEs in order to analyze the effects of AIID.The results from Column (5) and (6) of Table 8 reveal that the AIID program has a stronger negative effect on reducing carbon emission in non-state-owned firms compared to state-owned firms.

The effect of AIID on carbon reduction is relatively small in state-owned enterprises. State-owned enterprises are strongly policy-oriented and usually prioritize compliance rather than pursuing profit maximization. Therefore, they lack strong market-driven motivation when applying AI technology. In addition, state-owned enterprises have complex hierarchical management and long decision-making processes, which slows the implementation and promotion of AI technology. At the same time, they have long relied on traditional high-carbon production models, face strong path dependence, and are not easy to quickly switch to low-carbon technology. In contrast, non-state-owned enterprises are more driven by market competition pressure, have more flexible management, and are more willing to use AI technology to optimize production processes and improve energy efficiency to reduce costs and enhance market competitiveness. In addition, state-owned enterprises usually enjoy more government subsidies and have relatively less policy pressure on carbon reduction. Non-state-owned enterprises lack government support of the same scale and rely more on their own competitiveness, so they are more motivated to apply AI technology to achieve carbon reduction goals. At the same time, the carbon

emission targets of state-owned enterprises are usually set by the government and are subject to administrative regulation rather than market mechanism drive, resulting in limited actual role of AI technology in their carbon reduction. In contrast, non-state-owned enterprises need to directly face market carbon costs, such as carbon trading markets and green supply chain requirements, and therefore demonstrate more significant carbon emission reduction results when empowered by AI (Longsheng et al., 2024, Jian et al.,2023, Aiting et al., 2023).

5.Conclusions and implications

This study, viewed as a quasi-natural experiment, examines the impact of the AIID pilots in China. Using data from the Shanghai Stock Exchange and Shenzhen Stock Exchange for Chinese A-share manufacturing companies from 2015 to 2022, it employs the staggered-DID model to evaluate how the AIID pilots affect firms' carbon emissions reduction. The firms in the treatment group are then matched with those in the control group using the entropy balancing method. This paper further uses machine learning methods to testify results. I found the implementation of the AIID pilots has resulted in a significant decrease in the carbon emissions from firms that were covered by the pilots.

The findings of this study expand our understanding of the effectiveness and strategies of utilizing AIID to promote the reduction of carbon emissions and offer policymakers valuable information. The Chinese government should upgrade the infrastructure and associated procedures to boost the AIID's effectiveness and tighten the pertinent laws and regulations to promote cost-effective emissions reduction. I suggest that the government provide legislative incentives to promote the AIID's adoption, such as tax exemptions, credits, or subsidies for AI green innovation for businesses utilizing AI to more effectively cut emissions.

Despite the study's focus on the Chinese instance, I believe that other nations considering developing an AIID may find similar suggestions applicable as well. This study's shortcoming is that the AIID might have caused carbon leakage problems for businesses in various Chinese regions. AI-driven technologies that reduce emissions and save energy typically come with significant upfront expenditures (e.g., data processing costs, RD for AI systems, smart manufacturing equipment). Small and medium-sized businesses could have trouble covering these expenses. These businesses might decide to move to a different location in order to save money on the high costs of intelligent transformation. The impact of the AIID pilots on the carbon emissions intensity of enterprises may have been underestimated in this study, which could result in carbon leakage issues. Our next study intends to create a metric of enterprises' interconnectedness through equity penetration in order to assess the effect of the AIID on carbon leakage across various Chinese areas.

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