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How can AI reduce carbon emissions? Insights from a quasi-natural experiment using generalized random forest

Lingbing Feng [a,b,c], Jiajun Qi [d,*], Yuhao Zheng [e,*]

[a] School of Statistics and Data Science, Jiangxi University of Finance and Economics, Nanchang, Jiangxi 330013, China
[b] Key Laboratory of Data Science in Finance and Economics, Jiangxi University of Finance and Economics, Nanchang, Jiangxi 330013, China
[c] Research Centre for Financial Development and Risk Prevention, Jiangxi University of Finance and Economics, Nanchang, Jiangxi 330013, China
[d] School of Applied Economics, Jiangxi University of Finance and Economics, Nanchang, Jiangxi 330013, China
[e] School of Finance, Jiangxi University of Finance and Economics, Nanchang, Jiangxi 330013, China

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ABSTRACT

This study examines the impact of a recent regional artificial intelligence pilot zone (AIPZ) policy in China on firms' carbon performance using a quasi-natural experiment. Using the Difference-in-Differences (DID) methodology, the findings reveal that the AIPZ policy significantly reduces firms' carbon emissions. This effect is most pronounced for firms with high talent levels, positive media sentiment, and strong internal control, while heavily polluting firms experience a relatively minor effect. A variable importance analysis using the generalized random forest approach identifies return on assets (ROA) and Tobin's Q as significant contributors to the variation in firms' responses. Specifically, when ROA is negative, the treatment effect is relatively large and increases slowly. In contrast, when ROA is positive, the treatment effect decreases rapidly, showing a zero-boundary effect. Additionally, Tobin's Q exhibits an inverted U-shaped relationship with the treatment effect. The findings of this study offer valuable insights for policymakers in China and beyond, highlighting the importance of considering firm-specific characteristics to achieve effective and sustainable environmental management alongside economic development.

1. Introduction

With climate change as a major global concern, the contemporary world faces the daunting challenge of reducing carbon emissions. Large-scale carbon emissions are a leading cause of global warming, resulting in increased extreme weather events, rising sea levels, and loss of biodiversity (Chishti et al., 2024). According to the International Energy Agency (IEA), global energy–related carbon dioxide emissions have continued to rise over the past few decades, with significant carbon emissions growth in developing countries and emerging economies (Guo and Zhang, 2024). This trend places immense pressure on the global climate system and exacerbates environmental issues on a global scale.

With the rapid growth of the Chinese economy and accelerated industrialization, China's carbon emissions have increased exponentially over the past few decades (Zhu and Rao, 2024). China has been the world's largest carbon emitter since 2006 (He and Chen, 2023). According to the IEA's CO_2 Emissions in 2023 report, China's carbon emissions increased by approximately 565 million tons, marking the largest increase globally and contributing to about one-third of the global increase in carbon dioxide emissions in 2023. Considering China's unique status as the world's largest developing country and its responsibility as a major carbon emitter, in-depth studies of China's associated policy measures can provide crucial insights for governments worldwide. Moreover, such efforts can aid countries in better understanding how to strike a balance between economic development and environmental protection to collectively advance the global sustainable development agenda.

Despite a series of policies implemented by the Chinese government to address carbon emissions that have achieved some success (Zhou et al., 2024), previous research has found that such policies may lead to a decline in productivity (Deng and Li, 2020; Shi et al., 2022). This suggests that firms might be pressured to adopt production reduction strategies to meet emissions targets, resulting in economic performance losses. This approach, which sacrifices economic development for environmental improvement, clearly contradicts the core concept of sustainable development. Therefore, this study shifts the focus to a more

* Corresponding authors.
E-mail addresses: qijj0106@gmail.com (J. Qi), ehoole1203@foxmail.com (Y. Zheng).

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comprehensive carbon performance evaluation metric, measuring firm revenue per unit of carbon emissions. Compared with a single carbon emissions metric, the advantage of the carbon performance metric is its ability to reflect a firm's capacity to balance environmental responsibility with economic benefits, effectively avoiding the scenario in which firms pursue emissions reductions at the expense of economic efficiency, known as the "robbing Peter to pay Paul" phenomenon.

To improve firms' carbon performance, relevant regulations typically set stringent environmental standards and emissions targets, compelling firms to seek innovative solutions to reduce carbon emissions. For instance, the Paris Agreement set common goals for global carbon reduction, prompting governments and firms worldwide to take concerted action (Chishti et al., 2024). As a powerful technological tool, artificial intelligence (AI) has a crucial role in this process (Srivastava et al., 2023). AI has been employed in many countries for various tasks such as forecasting, monitoring, and big data analysis (Stef et al., 2023). Such applications not only help firms monitor and manage carbon emissions more accurately but also optimize production processes and enhance energy efficiency, achieving emissions reduction targets while maximizing economic performance (Ding et al., 2023). For instance, Google reduced management costs by 40 % using deep learning AI technology; an accomplishment that would have been difficult to achieve with traditional methods (Henderson et al., 2020). A study by McKinsey Global Institute determined AI could potentially increase global GDP growth by 1.2 % annually by 2030 (Bughin et al., 2018), surpassing the annual growth effects generated by the spread of steam engines and information technology (IT), which were 0.3 % and 0.6 %, respectively. Therefore, AI technology integration is expected to provide new ideas and solutions for enhancing carbon performance and achieving a mutually beneficial outcome for environmental and economic benefits. In recent years, the Chinese government has been committed to promoting AI technology, establishing the National New Generation AI Innovation Development Pilot Zones (AIPZ) with 18 cities in batches in 2019, 2020, and 2021. This policy aims to significantly advance the development and promotion of AI technology, enabling firms to use emerging AI technologies to improve energy efficiency and enhance economic performance while reducing carbon emissions. Therefore, investigating the impact of AIPZ policy implementation on firms' carbon performance is of great significance.

This study employs AIPZ implementation as a quasi-natural experiment using firm-level data to examine the policy's impact on firms' carbon performance. A multi-period difference-in-differences model is constructed to evaluate the policy's treatment effect, supported by robustness tests. The mechanism analysis reveals that talent, media tone, internal control, and pollution level influence policy outcomes. To explore heterogeneity, the study uses the generalized random forest (GRF) method, which offers more granular insights than traditional grouped regression. The findings show that AIPZ positively impacts carbon performance, particularly for firms with higher talent, more positive media sentiment, and better internal control, while heavily polluting firms weaken the effect. GRF results highlight return on assets (*ROA*) and Tobin's Q as key drivers of heterogeneity: a negative ROA enhances the treatment effect, while a positive ROA decreases it; Tobin's Q exhibits an inverted U-shaped relationship with the treatment effect.

This study makes several contributions to the literature. First, it pioneers the examination of the AIPZ program's impact on firms' carbon performance, exploring both potential mechanisms and heterogeneity, thereby advancing research in AI and energy. Second, unlike prior studies focusing solely on carbon emissions (Papp et al., 2023; Zhao et al., 2024), this study incorporates carbon performance indicators, comprehensively considering carbon emissions and firm revenue. Doğan et al. (2020) and Nasir et al. (2019) argued that economic growth should be considered when assessing carbon emissions, while Cao et al. (2021) and Shi et al. (2022) suggested that emissions reductions may result from passive factors like reduced production rather than technological improvements. While such measures can meet carbon reduction goals, they may harm economic development. Thus, focusing on carbon performance allows for a more comprehensive evaluation of policies, ensuring emissions reduction while promoting economic benefits. Finally, this study introduces machine learning, using the GRF method for causal identification and heterogeneity analysis, offering a novel perspective. Compared with traditional methods, GRF has two key advantages: it identifies the variables contributing most to heterogeneity, enabling more targeted analysis, and estimates treatment effects for individual firms, providing deeper insights into the relationship between heterogeneity factors and treatment effects to guide more precise policy recommendations.

The remaining sections of this paper are structured as follows. Section 2 provides a literature review and research hypotheses, Section 3 outlines the research design, Section 4 presents the empirical results and analysis, Section 5 delves into the mechanism analysis, Section 6 conducts heterogeneity analysis, and Section 7 presents the conclusion and policy implications.

2. Literature review and research hypotheses

2.1. Literature review

2.1.1. Carbon emissions reduction and environmental policies

Under increasing environmental pressures, the issue of carbon emissions reduction has become a popular research topic. Numerous studies have explored the impact of environmental policies or events on carbon emissions such as the establishment of the EU Emissions Trading System (Bel and Joseph, 2015), China's carbon emissions trading pilots (Xuan et al., 2020), green credit policies (Sun and Zeng, 2023), and low-carbon city pilots (Hou et al., 2023). Most studies have indicated that the implementation of these policies can indeed reduce firms' carbon emissions through positive measures such as promoting investment in research and development (R&D), green innovation, and improving energy efficiency (Hou et al., 2023; Zhang et al., 2020). However, some scholars have introduced opposing views, arguing that environmental regulations can impair firms' productivity, with the resulting carbon reduction effects primarily arising from negative factors like production cuts and emissions reduction (Cao et al., 2021; Shi et al., 2022). Therefore, a comprehensive evaluation of firms' environmental and economic performance is an urgent concern that helps assess the actual effects of policies and provides a scientific basis for firms' sustainable development.

2.1.2. Mixed effects of AI on economic and environmental performance

As environmental regulations become increasingly stringent, firms begin to seek new technologies to enhance environmental performance and economic efficiency. As a rapidly developing emerging technology, AI has been applied in various fields such as production, forecasting, and monitoring (Chen et al., 2022; Jha et al., 2017), attracting considerable interest from firms and scholars. Czarnitzki et al. (2023) used data from the German Innovation Survey and found that firms using at least one AI technology significantly improve productivity. Lee et al. (2022) adopted a similar approach, using survey data on respondents' ratings of AI adoption to measure AI adoption rates and verified a positive correlation between AI adoption and firm performance. Yang (2022) also corroborated this finding, using the number of AI patents to measure AI rates, and determined that AI development could promote firm performance improvement. Additionally, Mishra et al. (2022) used text analysis of firms' annual reports to measure AI focus, showing that firms with greater AI focus performed better.

As noted above, while most studies have indicated that AI development can enhance firms' economic performance, the impact of AI on firms' environmental performance has two sides. Some scholars have argued that AI can promote technological innovation, which improves energy efficiency and enhances firms' environmental performance. For example, Wang et al. (2024) used text analysis to measure firms' AI adoption rates and found that high AI usage rates promoted green innovation efficiency. Zhang and Zeng (2024) measured AI using industrial robot adoption and demonstrated that AI significantly reduced firms' energy intensity. Therefore, it has been convincingly demonstrated that AI can be an effective tool in addressing carbon emissions, but its potentially negative impacts should not be overlooked. Dhar (2020) noted that AI itself is also a significant source of carbon emissions, with processes like training models consuming substantial amounts of energy. Gaur et al. (2023) also showed that the training processes of AI models generate considerable carbon emissions. The authors calculated the carbon emissions of various machine learning and deep learning models in detail and encouraged the practice of sustainable AI. Therefore, the influence of AI on carbon emissions still requires further exploration.

2.1.3. Research gaps and study contributions

Summarizing the above literature analysis, first, previous research has predominantly focused on carbon emissions, while neglecting the development aspect of sustainable development. Second, the majority of studies have used methods such as text analysis and industrial robot usage to measure AI levels; however, these methods do not fully capture the overall concept of AI. Therefore, this study uses the carbon performance indicator as the research object, comprehensively considering firms' environmental and economic performance. The study also takes the impact of an AI-related policy as the starting point. AI policy implementation covers various aspects of AI development, providing a more comprehensive measure of firms' AI levels.

2.2. Policy background

As a burgeoning field of next-generation IT, AI has permeated many aspects of production and daily life, quietly transforming the operational modes of economic and social organizations. To promote the development of AI technology, China released the Guideline for the Construction of National New Generation AI Innovation Development Pilot Zones in 2019, officially launching pilot zones in batches at the prefecture level, with 18 pilot zone cities selected from 2019 to 2021. The first batch of pilots began in 2019, encompassing Beijing, Shanghai, Tianjin, Shenzhen, Hangzhou, Hefei, and Huzhou. The second batch started in 2020, specifying Chongqing, Chengdu, Xi'an, Jinan, Guangzhou, and Wuhan. The third batch commenced in 2021, covering Suzhou, Changsha, Zhengzhou, Shenyang, and Harbin. Although each city's positioning and development focus varied, such as Beijing being the first pilot city with the highest number of AI firms and aiming to become a hub for original AI innovation, and Hangzhou focusing on empowering urban governance with AI, which led to AI innovations like smart transportation and smart business districts, the overall objectives of the three batches are largely consistent. The primary goal is to build a favorable ecosystem for AI development and promote AI advancement. By collaborating with firms on AI innovation platform projects, these cities endeavor to achieve deep collaboration in AI, seek new paths for the coordinated development of AI and associated firms, explore new models of governance in the AI era, and propel AI to become a significant engine for economic development and social governance.

2.3. Research hypotheses

2.3.1. AI and firm carbon performance

Referencing the assertion by Borges et al. (2021) that AI may be the most disruptive force in technology today, and considering its profound impact on firms' sustainable development (Nishant et al., 2020), it is evident that China's AIPZ policy has significant implications for advancing regional and corporate AI proficiency as a significant initiative to promote AI innovation and enhance its capabilities. Through AI-enabled intelligent optimization and precision management, firms can effectively control energy consumption and material allocation in production processes (Dubey et al., 2020), thereby reducing energy and material waste (Shu et al., 2023; Yang, 2022) and subsequently lowering carbon emissions. Additionally, the data analysis and predictive capabilities of AI technology can help firms accurately assess current energy use circumstances (Ferrero Bermejo et al., 2019; González Ordiano et al., 2018) to formulate more effective carbon reduction strategies. By accurately analyzing and mining big data, AI can help firms gain insights into the sources and distribution patterns of carbon emissions, identify potential opportunities for emissions reduction and optimization, and provide precise evidence and decision support for firms (Sellak et al., 2017). Moreover, as societal awareness of environmental protection expands and demand for eco-friendly products grows, firms can leverage AI technology to develop more energy-efficient and environmentally friendly products and services, meeting market demands while reducing carbon emissions. Based on these considerations, this study proposes Hypothesis 1.

Hypothesis 1. The AI pilot zone policy significantly enhances firms' carbon performance.

2.3.2. The talent effect

Under the influence of the AIPZ policy, the talent effect may have a significant impact on firm carbon performance. First, high-level human resources typically possess stronger capabilities in technological innovation and application, with specialized knowledge and skills in the field of AI, which accelerates the development and application of new technologies (Awaworyi Churchill et al., 2019), enhancing firm carbon performance. Second, Goetz et al. (1998) and Graff Zivin and Neidell (2013) asserted that education contributes to changing people's behaviors toward nature, enabling the public to contribute to environmental improvement. Desha et al. (2015) also noted that education influences individuals' preferences for compliance with environmental regulations. Therefore, the advantage of high-level talent in management and decision-making can enable firms to plan and execute carbon reduction strategies more effectively (Blackman and Kildegaard, 2010; Zafar et al., 2019), adopt environmentally friendly technologies and management methods, and improve carbon performance. Additionally, high-level individuals have a strong sense of teamwork and knowledge sharing (Prada et al., 2022), which can promote technical exchange and cooperation within firms, accelerate the application of AI technology and innovations in carbon reduction technologies, and ultimately improving carbon performance. Therefore, high-level talent is expected to have a significant impact on the treatment effect of the policy. Therefore, this study proposes Hypothesis 2.

Hypothesis 2. The higher a firm's talent level is, the more significant the impact of the AI pilot zone policy will be on the firm's carbon performance.

2.3.3. Media sentiment

Firms' media coverage is a crucial channel for the public to obtain information (Hur et al., 2017) and is also a key factor in shaping corporate image. Previous research has predominantly focused on metrics of media attention such as the quantity of media coverage (Bissoondoyal-Bheenick et al., 2023), with limited exploration of the influence of media tone or attitude. The positivity or negativity of media coverage directly impacts a firm's reputation and image (Barreda et al., 2015), profoundly affecting its operations and development. Positive media coverage can enhance a firm's image and credibility in the public consciousness (Khalifa et al., 2024) as socially responsible and environmentally aware. Under the guidance of national policy, this positive image may further incentivize firms to increase investments and innovation to advance carbon reduction efforts. Moreover, positive media coverage also attracts more attention from investors and potential partners (Kim and Park, 2013; Nisar and Whitehead, 2016), providing firms with additional resources and support (Bushman et al., 2017). These investment and collaborative opportunities may provide firms with more technological and financial support, accelerating the advancement of AI-related projects and further improving carbon performance.

Conversely, negative media coverage may have various adverse effects on firms. First, negative coverage may damage a firm's public image and reputation (Dyck et al., 2008), leading to consumer distrust and affecting the firm's market position and competitiveness. Second, negative coverage may also increase firms' legal and policy risks (An et al., 2020), with local governments and regulatory agencies potentially intensifying oversight and restricting innovation and practices (Dai et al., 2021), which can reduce the policy's treatment effect. Therefore, this study proposes Hypothesis 3.

Hypothesis 3. The more positive a firm's media coverage is, the more significant the impact of the AI pilot zone policy will be on the firm's carbon performance.

2.3.4. *Firm internal control*

Due to the novelty and complexity of AI technology, not all firms are able to effectively integrate it into their operations. Brock and von Wangenheim (2019) noted that some firms may introduce AI technology into their operations without possessing the necessary internal capabilities. The quality of internal control reflects a firm's management level and risk management capabilities (Harasheh and Provasi, 2023), which may have significant implications for the magnitude of policy treatment effects. First, effective internal control enable firms to better comply with the requirements of AI policy and introduce AI technology and applications more quickly, which can optimize production processes (Boulhaga et al., 2023), improve efficiency (Morris, 2011), and even advance the development of intelligent technologies related to environmental protection to further reduce carbon emissions and enhance carbon performance. Second, effective internal control can ensure that firms consciously assume the social responsibility to protect the natural environment and resources (Al-Shaer and Zaman, 2018), which can enhance carbon performance. Additionally, efficient internal control can strengthen firms' supervision of internal and external information reception (Zhao et al., 2023) to manage risks related to AI more effectively. In the process of applying AI technology, risks related to data privacy protection, information security, and other concerns may arise (Habbal et al., 2024). Firms with good internal control can better manage these risks, ensuring data security and the smooth progress of technological applications, advancing firms' development under AI policy. Therefore, this study proposes Hypothesis 4.

Hypothesis 4. The better a firm's internal control is, the more significant the impact of the AI pilot zone policy will be on the firm's carbon performance.

2.3.5. *Firm pollution level*

Firms in heavily polluting industries are major sources of greenhouse gas (GHG) and crucial participants in environmental responsibility (Lin et al., 2021). Therefore, the firms' pollution level may also have a significant impact on AIPZ policy treatment effects. Xu and Li (2020) found that heavily polluting firms face greater financing pressure. Consequently, non-heavily polluting firms may find it easier to obtain external funding support, which can enable them to implement the policy more successfully to improve carbon performance. Furthermore, heavily polluting firms may face more intense social pressure and higher investment, environmental litigation, and reputational risks (Liu et al., 2019), which affect firms' ability and willingness to implement policy requirements. Additionally, heavily polluting firms often have a large number of fixed assets and production lines that require more funds to renovate and upgrade. These high costs can reduce the benefits that heavily polluting firms could receive from following policy mandates (Zhang and Vigne, 2021). Based on these considerations, this study proposes Hypothesis 5.

Hypothesis 5. The impact of the AI pilot zone policy on the carbon performance of non-heavily polluting firms is more significant than that on heavily polluting firms.

3. Research design

3.1. *Methodology*

3.1.1. *Benchmark model*

To evaluate the impact of the AIPZ policy on firms' carbon performance, this study treats the policy's implementation as a quasi-natural experiment, considering listed companies in the 18 cities that participated in the AIPZ program in 2019, 2020, and 2021 as the treatment group, and those in non-pilot areas as the control group, constructing the following multi-period DID model:

$$Carbon_{it} = \alpha + \beta AIPZ_{it} + \gamma Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where i represents the firm, and t represents the year. $Carbon_{it}$ denotes the carbon performance of firm i in year t. $AIPZ_{it}$ indicates whether firm i was subject to the AI pilot treatment in year t, where 1 signifies treatment and 0 otherwise. β measures the policy's treatment effect, $Control_{it}$ represents a series of control variables that may affect firm carbon performance, μ_i and λ_t are respective individual and year fixed effects, capturing firm-specific characteristics and time factors inherent to each firm respectively, and ε_{it} is the error term, which is assumed to be independently and identically distributed.

3.1.2. *Mechanism model*

To investigate how the AIPZ influences firm carbon performance, this study constructs the following model:

$$Carbon_{it} = \alpha + \beta_0 AIPZ_{it} + \beta_1 M_{it} + \beta_2 AIPZ_{it}{}^{*} M_{it} + \gamma Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

where M_{it} represents the moderating variable, and $AIPZ_{it}*M_{it}$ denotes the interaction term between the treatment indicator and the moderating variable. A significant β_2 coefficient indicates that the moderating variable indeed influences the treatment effect.

3.1.3. *GRF*

According to the potential outcome framework of Robins et al. (1994), Nie and Wager (2021) proposed the R-learner function. This function is intended to remove the influence of confounding factors and convert the estimation of treatment effects into an optimization problem of a loss function, allowing the incorporation of machine learning methods into causal inference. The functional expression is shown in Eq. (3).

$$\widehat{\tau}(\cdot) = argmin_{\tau}\left\{\frac{1}{n}\sum_{i=1}^{n}\left(\left(Y_i - \widehat{m}^{(-i)}(X_i)\right) - \left(W_i - \widehat{e}^{(-i)}(X_i)\right)\tau(X_i)\right)^2\right\} \tag{3}$$

where τ represents the treatment effect, and X_i denotes the characteristics of firm i; Y_i is the outcome variable of firm i, which is carbon performance in this study; and W_i indicates whether firm i is in the treatment group. $e(X_i) = P[W_i|X_i = x]$ represents the propensity score, which indicates the probability that firm i receives treatment given the covariate X_i, and $(-i)$ represents the out-of-bag estimate. $m^{(-i)}(X_i) = E[Y_i|x = X_i]$ denotes the predicted value of Y_i when the covariate is X_i. The treatment effect can be estimated for each training sample using Eq. (3). Subsequently, referencing Athey et al. (2019), this study constructs a GRF to estimate the treatment effect with the following steps:

1) Randomly sample subsets of both samples and features from the sample set.
2) Randomly split the sample subset into training and estimation sets at a 50 % ratio.

3) Use the training set to build causal trees, with the splitting rule maximizing the difference between nodes, as follows:

$$\Delta(C_1, C_2) = \frac{n_{C_1} n_{C_2}}{n_P^2} (\widehat{\theta}_{C_1} - \widehat{\theta}_{C_2})^2 \tag{4}$$

where P is the parent node of the tree, C_1 and C_2 are the split subnodes, $\widehat{\theta}$ is the average treatment effect of the two subnodes, and n is the sample size. The criterion for splitting is to maximize $\Delta(C_1, C_2)$, which means maximizing the heterogeneity between subnodes while balancing the difference in sample sizes between the two subnodes. Compared with traditional random forest models, the splitting rule of causal trees focuses on maximizing differences between nodes rather than minimizing prediction errors within nodes, which essentially highlights the heterogeneity of treatment effects.

4) Match the estimation set samples with the causal tree leaf nodes based on the feature X.
5) For each test sample (x), assign the same weights ($\alpha_{bi}(x)$) to training samples that fall into the same leaf node as x, which is expressed as follows:

$$\alpha_{bi}(x) = \frac{1(\{X_i \in L_b(X)\})}{|L_b(X)|} \tag{5}$$

where $L_b(X)$ is the set of training samples that fall into the same leaf node as x, and the denominator represents the number of samples in this training sample set. Therefore, in the entire GRF, the frequency $\alpha_i(x)$ of training sample i and test sample x falling into the same node can be calculated using Eq. (6). This represents the similarity between sample i and x and $\sum_{i=1}^{n} \alpha_i(x) = 1$.

$$\alpha_i(x) = \frac{1}{B} \sum_{b=1}^{B} \alpha_{bi}(x) \tag{6}$$

6) This study obtains the treatment effect estimate for x by weighting each sample.

The above steps are implemented using the **grf** package in the R programming language (Athey et al., 2019). We estimate the treatment effects for each individual firm using the GRF approach, which enables a more detailed and precise exploration of the relationship between covariates and treatment effects in heterogeneity analysis.

3.2. Variables definitions and data

3.2.1. Firm carbon performance

We divide the sample into two categories, according to firms' disclosure. The first category includes firms that directly disclose annual direct carbon emissions, indirect carbon emissions, or total carbon emissions. For these firms, we use the data that are directly disclosed in annual reports and standardize them into the same unit. The second category includes firms that do not directly disclose annual carbon emissions but provide data on different types of fossil energy consumption, electricity usage, heat usage, and other carbon-emitting forms. We calculate the carbon emissions for these firms by referencing the Guideline for Greenhouse Gas Emission Accounting and Reporting for Enterprises issued by China's National Development and Reform Commission.

After obtaining each firm's total carbon emissions, this study further uses the natural logarithm of revenue per unit of carbon emissions as a proxy variable for firm carbon performance (Perera et al., 2023). A higher value of this indicator implies better firm carbon performance. The specific calculation method is as follows:

$$Carbon\ performance = Ln\frac{Operating\ revenue}{Total\ carbon\ emissions} \tag{7}$$

3.2.2. Core independent variable

The core independent variable of this study is the AIPZ policy dummy variable. If a city implements an AIPZ project, the value of this variable for firms within that city is 1 in the pilot year and subsequent years, and 0 otherwise. If a city is not included in the list of AIPZ projects, the value remains 0 throughout the study period.

3.2.3. Control variables

Referencing Hou et al. (2023), Shang et al. (2023), and Zhang and Wang (2021), this study introduces a series of firm-level control variables. These include *Size*, representing the logarithm of total assets; *FirmAge*, which denotes the natural logarithm of the firm's age plus one; leverage (*Lev*), indicating the ratio of total liabilities to total assets; return on assets (*ROA*), which is calculated as the firm's net profit divided by its total assets; Tobin's Q (*TobinQ*), representing the market value of the firm relative to its asset replacement value; *Fixed*, denoting the ratio of net fixed assets to total assets; *Board*, which is measured by the natural logarithm of the number of board members; and Ownership Concentration (*Top*), indicating the proportion of total equity held by the largest shareholder. These variables collectively aim to capture various dimensions of firm characteristics and governance structures that could potentially influence the relationship between the AIPZ policy and firm carbon performance. Table 1 presents the variables' definitions.

3.3. Data source

The initial sample for this study includes A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2013 to 2022. Carbon emissions data are obtained from annual corporate social responsibility, sustainable development, and environmental reports disclosed by companies. Other data are sourced from the China Stock Market and Accounting Research database. This study excludes firms in the financial industry due to their unique regulatory and accounting standards. Additionally, ST and *ST firms are excluded because their operating conditions are abnormal, and they are flagged as high-risk by stock exchanges. Excluding these special samples enhances the credibility of this study's conclusions. Moreover, samples with missing key data are also excluded.

4. Empirical results and analysis

4.1. Descriptive statistics

Table 2 presents descriptive statistics of the main variables. Carbon performance ranges from a minimum of 3.883 to a maximum of 12.126, indicating significant variation in firms' carbon performance. The analysis of variables' correlation is presented in the **Appendix**.

Table 1
Variable definitions.

Variables	Definition	Description or calculation method
Carbon	Firm carbon performance	Natural logarithm of revenue per unit of carbon emissions.
AIPZ	Policy dummy variable	Equals 1 if a city implemented an AI pilot zone in the pilot year and subsequent years, otherwise 0
Size	Firm size	Natural logarithm of total assets
FirmAge	Firm age	Natural logarithm of firm age plus one year
Lev	Leverage ratio	Ratio of total liabilities to total assets
ROA	Return on assets	Net profit divided by total assets
TobinQ	Tobin's Q	Firms' market value divided by asset replacement value
Fixed	Fixed asset ratio	Net fixed assets divided by total assets
Board	Board size	Natural logarithm of the number of board members
Top	Ownership concentration	Proportion of shares held by the largest shareholder

Table 2
Descriptive statistics.

Variables	Observations	Mean	Std.Dev	Min	Max
Carbon	22,632	8.249	0.564	3.883	12.126
AIPZ	22,632	0.193	0.395	0.000	1.000
Size	22,632	22.376	1.328	19.59	26.452
FirmAge	22,632	2.965	0.303	1.792	3.611
Lev	22,632	0.424	0.199	0.046	0.908
ROA	22,632	0.042	0.064	−0.373	0.247
TobinQ	22,632	2.027	1.336	0.802	15.607
Fixed	22,632	0.226	0.154	0.002	0.719
Board	22,632	2.117	0.195	1.609	2.708
Top	22,632	34.232	14.586	8.020	75.525

4.2. Benchmark regression results

Based on the model design and variable selection previously outlined, this section investigates the impact of AIPZ projects on firms' carbon performance. Table 3 presents the results of the baseline regression. In column (1), without incorporating fixed effects or control variables, the estimated coefficient is 0.3417, which is significant at the 1 % level. In column (2), introducing control variables, the coefficient of the AIPZ policy decreases but remains significantly positive. In column (3), further controlling for firm and year fixed effects, the coefficient of the AIPZ policy decreases to 0.0208, indicating that AIPZ implementation results in an average 2.08 % increase in firms' carbon performance. Incorporating control variables and fixed effects into the model captures the various factors that influence the dependent variable more comprehensively, which reduces the impact of potential omitted variable bias. Specifically, adding control variables and fixed effects isolates the net effect of the AIPZ policy on the dependent variable. Integrating these model improvements reveals a significant reduction in the AIPZ coefficient, indicating that uncontrolled factors were indeed present in the initial model. This also suggests that the chosen control variables and fixed effects effectively absorb the influence of unobservable factors on firms' carbon performance. Additionally, the adjusted R-squared value gradually rises as control variables and fixed effects are included,

Table 3
Benchmark regression results.

	(1)	(2)	(3)
	Carbon	Carbon	Carbon
AIPZ	0.3417***	0.3076***	0.0208***
	(0.0056)	(0.0064)	(0.0057)
Size		0.0127***	0.0426***
		(0.0028)	(0.0089)
FirmAge		0.2610***	0.0461
		(0.0092)	(0.0387)
Lev		−0.0854***	0.0596***
		(0.0206)	(0.0217)
ROA		−0.0811	0.1506***
		(0.0617)	(0.0345)
TobinQ		−0.0199***	0.0001
		(0.0023)	(0.0018)
Fixed		−0.0046	0.0335
		(0.0195)	(0.0317)
Board		−0.1502***	0.0058
		(0.0157)	(0.0175)
Top		−0.0018***	0.0010**
		(0.0002)	(0.0004)
Constant	8.1832***	7.5926***	7.0682***
	(0.0024)	(0.0642)	(0.2351)
Observations	22,632	22,632	22,632
Adjusted R-squared	0.057	0.083	0.888
Firm FE	NO	NO	YES
Year FE	NO	NO	YES

Note: *, **, and *** indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively. Firm and Year FE stand for firm and year fixed effects, respectively. Standard errors, clustered at the firm level, are reported in parentheses.

demonstrating that the added variables enhance the explanatory power of the model.

The results indicate that the AIPZ policy can significantly improve firms' carbon performance. This improvement may be attributable to the introduction of AI technologies, which can help firms optimize production processes, increase energy efficiency, and reduce resource waste. Additionally, when firms introduce AI technologies, they typically engage in internal process optimization, such as adjusting operational strategies and investing in green technologies, which further enhances carbon performance. We discuss these mechanisms in more detail in the mechanism analysis section.

4.3. Robustness tests

4.3.1. Parallel trend test

The prerequisite for using DID is the requirement that control and treatment groups satisfy the parallel trend assumption, confirming that both groups exhibit parallel development trends prior to AIPZ implementation. If the trends are not consistent, the regression results may be biased. Referencing Beck et al. (2010), we employ the event study method to test dynamic processing effects and construct the following model:

$$Carbon_{it} = \alpha + \sum_{n=-6}^{3} \beta_n AIPZ_{it}^{n} + \gamma Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{8}$$

where n represents the time interval before and after the policy's pilot year. $AIPZ_{it}^{n}$ is the relative year policy variable generated with the reference year being the pilot project implementation year. β_n is the regression coefficient for the relative base year. $Control_{it}$ represents the control variables that may affect the firm's carbon performance. μ_i and λ_t are individual and year fixed effects, respectively. ε_{it} denotes the error term. If the coefficient of AIPZ before policy implementation is significant, this indicates a significant difference in control and treatment groups' carbon performance before policy implementation, violating the prerequisite of the DID method. This model can also examine the lagged effects of the policy.

This study selects the period immediately before policy implementation as the baseline, presenting the results in Fig. 1. The figure illustrates no significant difference in carbon performance between control and treatment groups prior to policy implementation. In the first year after policy implementation, the estimated coefficient does not

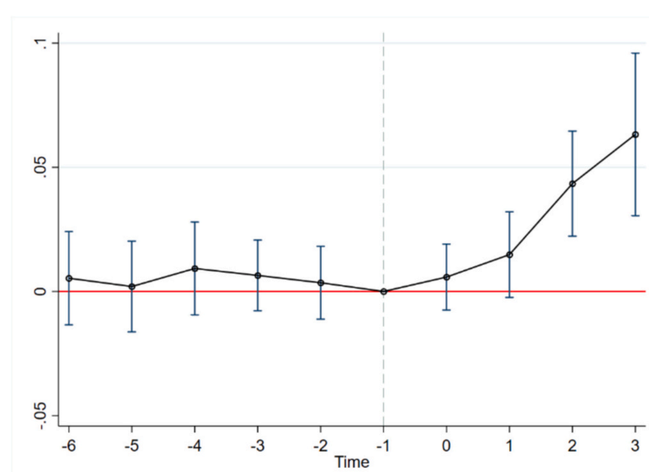

Fig. 1. Parallel trend graph at a 95 % confidence level.
Note: The horizontal axis represents relative years, ranging from −6 to −2 for the 5 years prior to policy implementation, 0 for the year of policy implementation, and 1 to 3 for the first to third years following policy implementation.

significantly differ from 0; however, from the second year onward, the policy effect becomes increasingly evident. This indicates that the AIPZ policy indeed promotes firms' carbon performance improvement, albeit with a lag effect. The rationale for this outcome might be that while AI encourages firms to adopt new technologies or change production methods to reduce carbon emissions, these changes may require some time for investment, construction, and implementation. For instance, firms may need to purchase new equipment, train employees, or redesign production processes. These investments and processes may result in the policy's effect on improving carbon performance lagging behind its implementation.

4.3.2. Sensitivity testing of parallel trend

Roth et al. (2023) argued that pre-trend tests alone are insufficient as effective empirical evidence for confirming the validity of the parallel trend assumption, as they do not guarantee that the treatment and control groups will still exhibit parallel trends in the actual post-policy years when no policy occurs. Building upon this, Rambachan and Roth (2023) proposed a method for sensitivity analysis when the parallel trend assumption might be violated, introducing two approaches based on pre-trend estimates of differences between the treatment and control groups.

The first approach is **Bounds on Relative Magnitude**, which estimates the extent to which post-treatment violations of parallel trends deviate relative to the maximum pretreatment parallel trend violation observed to test whether effects persist in the presence of post-treatment deviations from parallel trends. The second approach is **Smoothness Restriction**, which assesses how sensitive the estimated treatment effect is to deviations from pretreatment parallel trends.

This study tests significant post-treatment periods (post_2 and post_3) using bounds on relative magnitude and smoothness restriction. Based on bounds on relative magnitude, Fig. 2 and Fig. 3 respectively present the test results for post_2 and post_3, revealing that even when post-treatment parallel trends deviate by 50 %, the coefficients remain significant. Fig. 4 and Fig. 5 present the test results based on smoothness restriction, revealing that even with a pre-treatment trend deviation of 20 %, the effect persists. In summary, the two sensitivity analysis methods indicate that even when we allow for large deviations in parallel trends, our results remain significant and robust.

4.3.3. Heterogeneous treatment effect test

Many econometric studies have revealed heterogeneous treatment effects in the context of staggered DID with two-way fixed effects, which may affect the credibility of our estimation results (Goodman-Bacon, 2021). de Chaisemartin and D'Haultfœuille (2020) proposed a solution. The general approach is to first estimate the weights for each sample using a two-way fixed effects regression, where samples with negative weights may introduce bias. Second, we obtain an unbiased estimate of the policy effect through weighted averaging.

This study examines potential heterogeneous treatment effects in the baseline regression using heterogeneous robust estimators proposed by de Chaisemartin and D'Haultfœuille (2020). Fig. 6 presents the event study graph based on the heterogeneous robust estimators. The policy effect is not significantly evident prior to the AIPZ policy implementation; however, after policy implementation, the policy effect gradually emerges and reaches a relatively high level in the third year. These results are largely consistent with the sign, magnitude, and trend of treatment effects shown in the baseline regression, demonstrating the robustness of our conclusions.

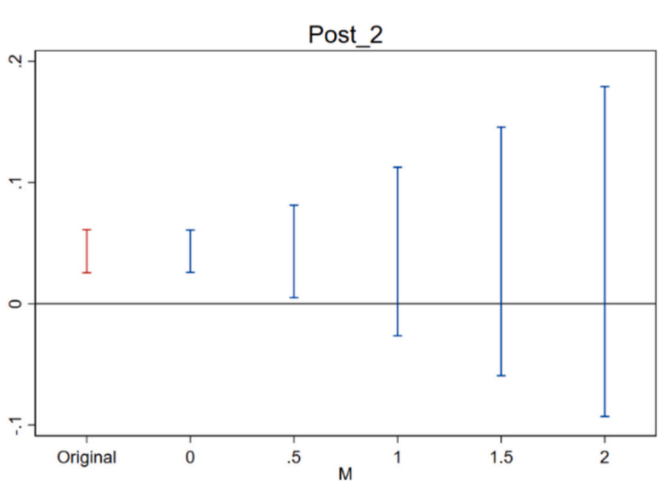

Fig. 2. Bounds on relative magnitude test for post_2.
Note: The horizontal axis represents the degree of deviation of parallel trends after processing. The red vertical lines represent the confidence intervals of the ordinary least squares regression, and the blue vertical lines represent the confidence intervals that vary with the degree of deviation.

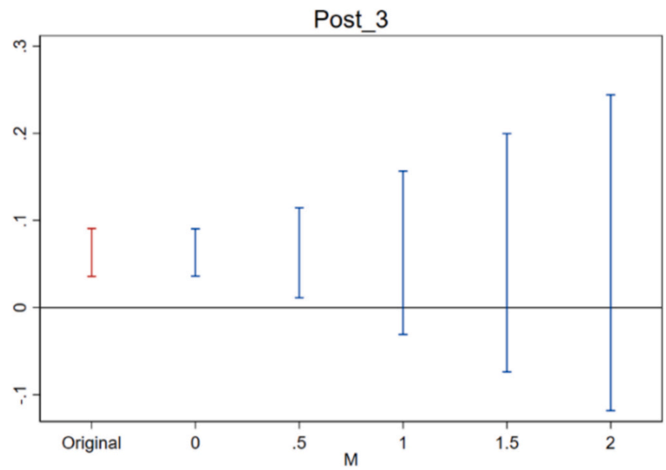

Fig. 3. Bounds on relative magnitude test for post_3.
Note: The horizontal axis represents the degree of deviation of parallel trends after processing. The red vertical lines represent the confidence intervals of the ordinary least squares regression, and the blue vertical lines represent the confidence intervals that vary with the degree of deviation.

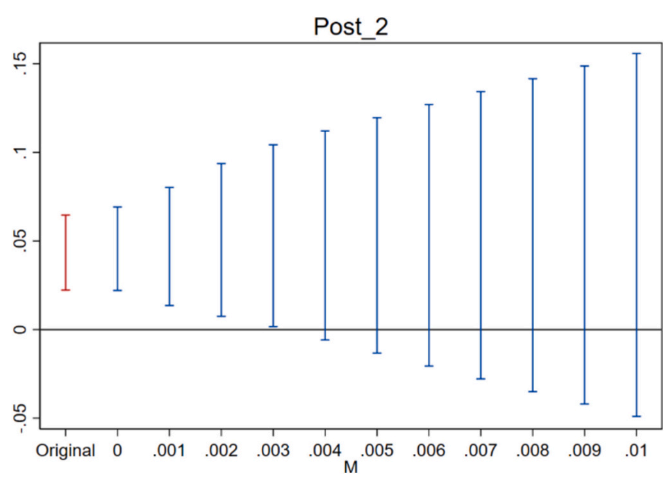

Fig. 4. Smoothness restriction test for post_2.
Note: Referencing Biasi and Sarsons (2022), M is set to 1 standard deviation. The red vertical lines represent the confidence intervals of the ordinary least squares regression, and the blue vertical lines represent the confidence intervals that vary with the degree of deviation.

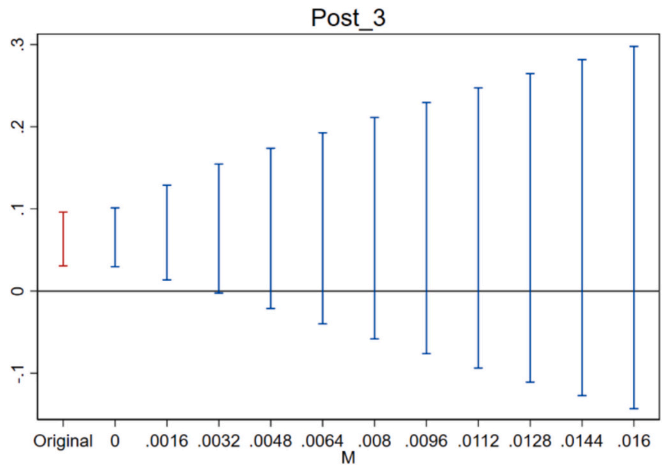

Fig. 5. Smoothness restriction test for post_3.
Note: Referencing Biasi and Sarsons (2022), M is set to 1 standard deviation. The red vertical lines represent the confidence intervals of the ordinary least squares regression, and the blue vertical lines represent the confidence intervals that vary with the degree of deviation.

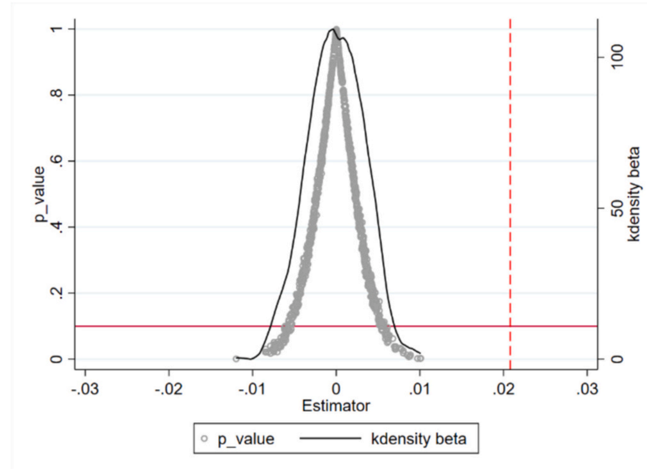

Fig. 7. Placebo test.
Note: The horizontal axis represents the estimated coefficients of pseudo-policy dummy variables. The solid red horizontal line indicates $p = 0.1$, and the vertical dashed red line represents the estimated coefficient of the true policy dummy variable (AIPZ).

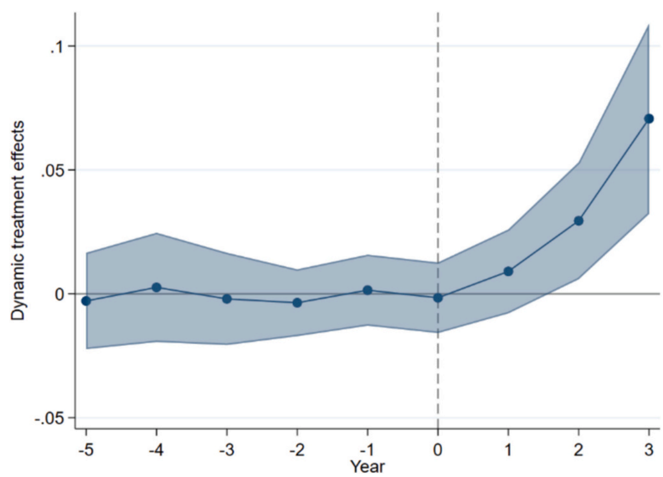

Fig. 6. Heterogeneous event study.
Note: The horizontal axis represents relative years, and the shaded area denotes the confidence interval.

4.3.4. *Placebo test*

This study also conducts a placebo test to further mitigate the impact of unobservable factors on the empirical results (Cai et al., 2016). Rather than assigning the firms located in the pilot cities as the treatment group, we randomly allocate firms. We then randomly select pilot timing within the sample period. We repeat this sampling process 1000 times, and use the baseline model for regressions. Since the virtual variables are constructed through random sampling, they should be unrelated to our dependent variable (firm carbon performance), indicating that the difference in estimation coefficients from 0 is not significant.

Fig. 7 illustrates the distribution of regression coefficients obtained from 1000 random samplings. The regression coefficients of the fabricated policy dummy variables predominantly cluster around 0 and exhibit a normal distribution. In contrast, the regression coefficient of the actual policy dummy variable is a clear outlier, consistent with the expectations of the placebo test.

4.3.5. *PSM-DID*

Sample selection bias may be evident due to differences in firms' development levels across different regions, which could affect the accurate assessment of policy effects. Therefore, this study employs the propensity score matching-DID (PSM-DID) method to enhance the comparability between firms in pilot and non-pilot regions. We employ four matching methods to ensure the robustness of the matching results, encompassing nearest neighbor matching, radius matching, kernel matching, and local linear matching. Specifically, the control variables used in the baseline regression are employed as covariates, and a logit regression is conducted to predict the probability of each firm becoming a pilot firm. Subsequently, various matching methods are employed to match treatment and control group samples to reduce the endogeneity issues caused by self-selection bias during the establishment of the AIPZ policy. Finally, regressions are performed based on the matched samples.

Table 4 reports the PSM-DID regression results. Columns (1)–(4) respectively present the results after nearest neighbor matching, radius matching, kernel matching, and local linear matching. The regression coefficients of AIPZ are significantly positive under all four matching methods, further confirming the robustness of the study's baseline conclusions that the AIPZ policy can significantly promote firms' carbon performance improvement.

4.3.6. *Excludes interference from other policies*

To rule out the interference of other policies that might affect firms' carbon performance and misidentify the policy effect, we reference Yang

Table 4
PSM-DID.

	(1)	(2)	(3)	(4)
	Nearest neighbor	Radius	Kernel	Local linear
	Carbon	Carbon	Carbon	Carbon
AIPZ	0.0224**	0.0208***	0.0208***	0.0239**
	(0.0102)	(0.0057)	(0.0057)	(0.0117)
Constant	6.9224***	7.0356***	7.0682***	6.7404***
	(0.5021)	(0.2451)	(0.2351)	(0.5507)
Observations	8234	22,566	22,632	7379
Adjusted R-squared	0.904	0.888	0.888	0.903
Control variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: *, **, and *** indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively. Firm and Year FE stand for firm and year fixed effects, respectively. Standard errors, clustered at the firm level, are reported in parentheses.

et al. (2023), introducing dummy variables that represent the implementation of other policies in the regression to control for their impact. If the dummy variable representing the AIPZ remains significant after including these control variables, this will further confirm the robustness of our conclusions. The specific steps are described below.

In 2013, the Chinese State Council issued and implemented the Action Plan for the Prevention and Control of Air Pollution to address China's increasingly severe air pollution problems. This action plan is a significant measure of the Chinese government in the field of environmental protection and a comprehensive plan for air pollution control, which may have an impact on firms' carbon performance. To control for its influence, this study constructs a dummy variable representing this policy to identify firms affected by the action plan, which takes the value of 1 for the year of implementation and each subsequent year, and 0 otherwise. After adding the virtual variable representing this policy (*policy_1*) to the regression, column (1) of Table 5 shows that the coefficient of AIPZ remains significantly positive. This indicates that the action plan has a relatively small impact on the empirical conclusions of this study.

In 2013 and 2016, China launched a pilot carbon emissions trading policy, which may also affect firm carbon performance. To eliminate potential interference of the carbon emissions trading pilot policy on the empirical results of this study, we construct a dummy variable representing this policy (*policy_2*) and introduce it into the baseline regression. The results in column (2) of Table 5 show that the coefficient of AIPZ remains significantly positive, indicating that the carbon emissions trading pilot policy did not interfere excessively with the study's baseline conclusions.

In 2014, the Chinese Ministry of Environmental Protection issued the Interim Measures for the Ministry of Environmental Protection's Interviews, which involved interviewing local government leaders responsible for environmental protection duties to strengthen the supervision of environmental violations and promote regulatory oversight related to environmental protection. To eliminate the impact of environmental interviews, we construct a dummy variable representing this policy (*policy_3*) and introduce it into the baseline regression. Column (3) of Table 5 presents the regression results, with the coefficient of AIPZ remaining significantly positive, indicating that environmental interviews did not significantly impact the conclusions of this study.

In 2017, 2019, and 2022, the Chinese State Council successively established Green Finance Reform and Innovation Pilot Zones in batches to reduce pollution emissions from enterprises within zones' jurisdiction and promote enterprises' green transformation, which may have affected firms' carbon performance. Therefore, we introduce a dummy variable representing this policy (*policy_4*) into the regression. Column (4) of Table 5 shows that the coefficient of AIPZ remains significantly positive, indicating that the Green Finance Reform and Innovation Pilot Zones policy had a relatively small impact on the conclusions of this study.

Table 5
Excluding interference from other policies.

	(1)	(2)	(3)	(4)
	Carbon	Carbon	Carbon	Carbon
AIPZ	0.0209***	0.0207***	0.0206***	0.0202***
	(0.0057)	(0.0057)	(0.0057)	(0.0057)
policy_1	−0.0152			
	(0.0352)			
policy_2		−0.0033		
		(0.0190)		
policy_3			−0.0186	
			(0.0175)	
policy_4				0.0387**
				(0.0159)
Constant	7.0772***	7.0692***	7.0747***	7.0595***
	(0.2272)	(0.2372)	(0.2319)	(0.2351)
Observations	22,632	22,632	22,632	22,632
Adjusted R-squared	0.888	0.888	0.888	0.888
Control variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: *, **, and *** indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively. Firm and Year FE stand for firm and year fixed effects, respectively. Standard errors, clustered at the firm level, are reported in parentheses.

4.3.7. *Other robustness tests*

Additional robustness tests include the following:

4.3.7.1. Replacing the explained variable. We replace the explained variable of firm carbon performance with firm carbon emissions, which is measured by the natural logarithm of total carbon emissions (*Carbon_b*). Column (1) of Table 6 reports the regression results, where the coefficient of AIPZ is significantly negative, confirming that the AIPZ policy indeed reduces firm carbon emissions, providing robust evidence for the conclusion of this study.

4.3.7.2. Lagging control variables by one period. To mitigate reverse causality concerns, we lag all control variables by one period before regression. The results are shown in column (2) of Table 6, and the coefficient of AIPZ is significantly positive, validating the robustness of the baseline conclusions.

4.3.7.3. Further controlling for industry fixed effects. Firm carbon performance may vary across different industries; for example, the carbon emissions of heavily polluting firms are certainly much higher than those of non-heavily polluting firms. Therefore, this study further controls for industry fixed effects in the regression. Column (3) of Table 6 shows that the coefficient of AIPZ policy is significantly positive, confirming the robustness of the conclusions.

4.3.7.4. Removing samples from the pilot year. In the baseline regression, we consider the pilot year and subsequent years as post-policy implementation. For robustness, we exclude samples from the policy implementation year and rerun the regression. The results in column (4) of Table 6 show that the coefficient of AIPZ remains significantly positive.

The above robustness tests further demonstrate the robustness of the baseline conclusion of this study, confirming that AI can significantly promote firms' emissions reduction and efficiency improvement.

5. Mechanism analysis

5.1. *Talent effect*

The baseline regression results indicate that the AIPZ policy significantly improves firms' carbon performance, but how it influences carbon performance remains to be examined. One possible key factor is the

Table 6
Other robustness tests.

	(1)	(2)	(3)	(4)
	Carbon_b	Carbon	Carbon	Carbon
AIPZ	−0.0514***	0.0187***	0.0212***	0.0390***
	(0.0136)	(0.0063)	(0.0057)	(0.0089)
Constant	−7.2022***	7.1379***	7.1701***	7.1908***
	(0.4709)	(0.3038)	(0.1938)	(0.2506)
Observations	22,632	18,725	22,630	17,461
Adjusted R-squared	0.956	0.888	0.889	0.896
Control variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	NO	NO	YES	NO

Note: *, **, and *** indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively. Firm and Year FE stand for firm and year fixed effects, respectively. Standard errors, clustered at the firm level, are reported in parentheses.

talent effect. The introduction and application of AI technologies often requires firms to have a workforce with the relevant expertise and skills that can effectively operate and manage AI technologies and promote carbon reduction concepts and practices within the firm to enhance overall carbon performance. Such talent might optimize algorithms, improve production processes, and propose innovative carbon reduction strategies, directly or indirectly promoting firms' carbon performance.

Previous research has explored the impact of the number of R&D personnel and employees with financial backgrounds on firm performance (Custódio and Metzger, 2014; Zhang et al., 2023), demonstrating that employees' abilities or backgrounds can indeed affect firm development; however, these indicators are insufficient for measuring the impact of AI. While the number of R&D personnel can reflect a firm's investment in technological innovation, it does not fully capture employees' ability to operate and manage AI technologies. Furthermore, the number of employees with financial backgrounds reflects the firm's expertise in finance and risk management, which is not directly related to AI implementation.

Therefore, to examine the moderating effect of the talent effect, this study uses the proportion of employees with postgraduate degrees or above to the total number of employees to measure the degree of high-level talent (*Postgraduate*). The rationale for this choice is threefold. First, employees with postgraduate degrees or higher typically receive more systematic and in-depth professional knowledge training, making them more likely to have the skills needed to operate and manage AI technologies (Awaworyi Churchill et al., 2019). Second, highly educated employees often demonstrate stronger learning capabilities and innovative thinking, enabling them to quickly adapt to and master new carbon reduction technologies and strategies, thereby fostering carbon reduction practices within the firm. Finally, highly educated employees often hold key positions within the firm (Blackman and Kildegaard, 2010), and their practices and decisions can significantly impact the firm's overall carbon performance.

We incorporate the interaction term between the degree of high-level talent and the policy dummy variable (*AIPZ*Postgraduate*) into the regression, presenting the results in column (1) of Table 7. The coefficient of the interaction term is significantly positive, indicating that high-level talent can promote the impact of AI on firms' carbon performance. In other words, the more high-level human resources the firm employs, the more pronounced the effect of AI will be on enhancing carbon performance.

Table 7
Mechanism analysis.

	(1)	(2)	(3)	(4)
	Carbon	Carbon	Carbon	Carbon
*AIPZ*Postgraduate*	0.0020**			
	(0.0010)			
*AIPZ*Media*		0.0285***		
		(0.0088)		
*AIPZ*InternalControl*			0.0090*	
			(0.0052)	
*AIPZ*Pollute*				−0.0292***
				(0.0113)
Postgraduate	0.0010			
	(0.0015)			
Media		−0.0092**		
		(0.0041)		
InternalControl			0.0025	
			(0.0022)	
Pollute				−0.0322
				(0.0254)
AIPZ	0.0055	0.0077	0.0217***	0.0252***
	(0.0082)	(0.0071)	(0.0057)	(0.0062)
Constant	7.1935***	7.1233***	7.0799***	7.0712***
	(0.2458)	(0.2397)	(0.2396)	(0.2333)
Observations	16,937	21,920	22,247	22,632
Adjusted R-squared	0.891	0.886	0.887	0.888
Control variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: *, **, and *** indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively. Firm and Year FE stand for firm and year fixed effects, respectively. Standard errors, clustered at the firm level, are reported in parentheses.

5.2. Media sentiment

The role of media attention as a mechanism of influence has been widely explored in previous research (Bissoondoyal-Bheenick et al., 2023). This study deepens this field by examining media attention through a more refined lens; specifically, by differentiating between positive and negative attention to analyze how media sentiment influences policy effects. To investigate the impact of media sentiment, this study references Clarkson et al. (2008), employing the Janis–Fadner coefficient to measure the media's attitude concerning firms. The calculation method for the Janis–Fadner coefficient is as follows:

$$Janis-Fadner=\begin{cases}\dfrac{e^2-ec}{t^2} & if\ e>c,\\ \dfrac{ec-c^2}{t^2} & if\ c>e,\\ 0 & if\ e=c.\end{cases} \tag{9}$$

where e represents the number of positive media reports, c represents the number of negative media reports, and $t = e + c$. Therefore, the Janis–Fadner coefficient ranges from −1 to 1. A coefficient closer to 1 indicates a more positive media attitude toward the firm, a coefficient closer to −1 indicates a more negative media attitude, and a coefficient of 0 suggests a neutral stance by the media toward the firm. The count of media reports is obtained from the CNRDS database.

After obtaining the Janis–Fadner coefficient, we introduce the interaction term of this coefficient with the policy dummy variable (*AIPZ*Media*) into the regression. The results in column (2) of Table 7 show that the coefficient of the interaction term is significantly positive. This indicates that more positive media coverage amplifies the positive impact of AI on firms' carbon performance. Positive media attention can enhance public awareness and acceptance of firms' AI-driven environmental measures, encouraging firms to further implement and promote these technologies. Additionally, positive media coverage can boost corporate management's confidence and determination, leading to the investment of more resources and effort in AI-driven environmental projects. A favorable public opinion environment may also attract more investments and policy support, providing firms with additional resources and technology to further improve their carbon performance.

5.3. Firms' internal control

Previous research has validated the importance of internal control in corporate performance (Vu and Nga, 2022); therefore, we hypothesize that a firm's level of internal control may also have a critical influence on how AI affects carbon performance. Firms with higher internal control typically have more comprehensive management systems and procedures, which enable more effective implementation and monitoring of AI technologies. In such firms, AI technologies are more likely to be distributed and used efficiently, maximizing their potential to improve carbon performance. Additionally, firms with strong internal control have superior information systems and risk management mechanisms that can swiftly identify and address issues that may arise during AI application to ensure projects' smooth progress. Moreover, firms with robust internal control often possess stronger compliance awareness and management capacities that allow them to better adapt to policy and market changes, optimize resource allocation, and enhance the efficiency and effectiveness of AI technology applications.

To explore the influence of internal control, we obtain firms' internal control data from the DIB database and introduce the interaction term between the policy dummy variable and internal control level (*AIPZ*InternalControl*) into the regression. Column (3) of Table 7 shows that the interaction term's coefficient is significantly positive, indicating that firms with higher internal control benefit more from AI in terms of improved carbon performance.

5.4. Heavily polluting firms

As this study focuses on firms' carbon performance, it is reasonable to posit that the degree of pollution a firm generates could also affect the AIPZ policy's treatment effect. Previous research has investigated the impact of environmental regulations on heavily polluting firms (Cheng et al., 2022). Therefore, we hypothesize that a firm's pollution level may influence the emissions reduction effect of the AIPZ policy. Heavily polluting firms often rely on traditional high-energy, high-emissions production technologies. Achieving a low-carbon transition requires the introduction of more advanced and environmentally friendly production processes and equipment, which incur higher costs compared with non-heavily polluting firms. Additionally, the transition process may face challenges such as skill mismatches among employees and production line adjustments, increasing the difficulty and uncertainty of such transitions, which can limit the effectiveness of AI technologies in improving carbon performance. Furthermore, as heavily polluting firms are key targets for environmental governance, they are subject to stricter environmental regulations and more stringent policy enforcement. Faced with strict emissions reduction targets, these firms may need to allocate more resources to meet compliance requirements rather than directly investing in AI technologies to improve carbon performance. This compliance expenditure could crowd out resources that could otherwise be used for technological innovation and energy conservation, diminishing the effectiveness of the policy.

To test this hypothesis, we created a pollution dummy variable (*Pollute*), assigning heavily polluting firms a value of 1 and non-heavily polluting firms a value of 0. We then introduced the interaction term between the policy dummy variable and the pollution dummy variable (*AIPZ*Pollute*) into the regression. Column (4) of Table 7 shows that the interaction term's coefficient is significantly negative, indicating that AI has a smaller impact on improving heavily polluting firms' carbon performance compared with non-heavily polluting firms.

6. Heterogeneity analysis using GRF

6.1. Estimated average treatment effect

This study employs GRF to estimate the treatment effect of the AIPZ policy, using the **grf** package in R for modeling analysis (Athey et al., 2019), with the number of trees set to 5000 and 10,000. Other parameters such as tree depth and minimum node size are determined by the package's automated tuning process. Table 8 presents the treatment effect estimation results based on GRF. The treatment effect of the AIPZ policy is significantly positive, which is consistent with the findings of the baseline analysis, indicating that the AI pilot policy can significantly improve firms' carbon performance.

Additionally, we also estimate the treatment effects for each firm using GRF, as shown in Fig. 8. The graph reveals that the treatment

Table 8
Generalized random forest.

	Carbon	Carbon
ATE	0.323***	0.323***
	(0.019)	(0.019)
Cluster	YES	YES
Trees	5000	10,000

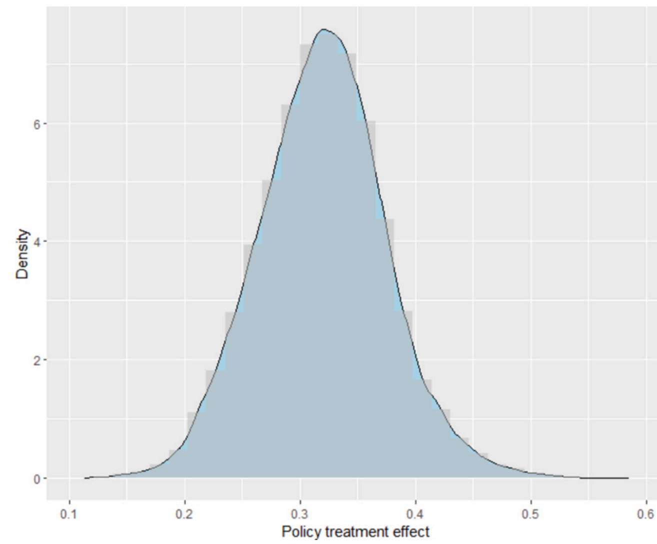

Fig. 8. Individual firms' treatment effect distribution.
Note: The horizontal axis represents individual treatment effects, and the vertical axis represents density.

effects for all firms are greater than 0, indicating a significant promotional effect from the AIPZ policy on improving firms' carbon performance. Furthermore, the majority of firms exhibit treatment effects ranging from 0.25 to 0.4, while the overall sample's treatment effects range from 0.1 to 0.6. This suggests significant variation in treatment effects across different firms, which warrants further analysis.

6.2. Selecting heterogeneous variables

After identifying significant differences in treatment effects between firms, we endeavor to identify the features associated with the maximum heterogeneity in treatment effects. In other words, we seek to determine which features lead to more pronounced heterogeneity between firms. To investigate this, we use the variable importance feature in the **grf** package to select the factors that contribute most to heterogeneity, which is calculated as follows:

$$importance_i = \frac{\sum_{l=1}^{L} \left(\frac{\sum_{n=1}^{N} \textit{The number of splits on feature i in tree n at layer l}}{\sum_{n=1}^{N} \textit{Total number of splits in tree n at layer l}} \right) \times l^{-2}}{\sum_{l=1}^{L} l^{-2}} \tag{10}$$

where l represents the layer, L is the maximum depth of the tree, B is the total number of trees, and i denotes the series of heterogeneous features included in the regression. For each feature i, we compute the proportion of splits based on feature i at each layer over the total number of splits and adjust the importance weights of different levels using l^{-2}. Finally, we obtain the importance score for each heterogeneous feature i by weighted averaging. As shown in Fig. 9, *ROA* and *TobinQ* are the two features with the highest weights. This indicates that these two features contribute significantly to the heterogeneity in treatment effects between firms; therefore, we use these features for further heterogeneity analysis.

6.3. Heterogeneity analysis results

6.3.1. Heterogeneity based on ROA

Fig. 10 illustrates the variation in policy treatment effects with changes in *ROA*. When ROA is less than 0, the treatment effect is relatively high and exhibits a slow upward trend; however, when ROA exceeds 0, the treatment effect significantly declines. This trend can be

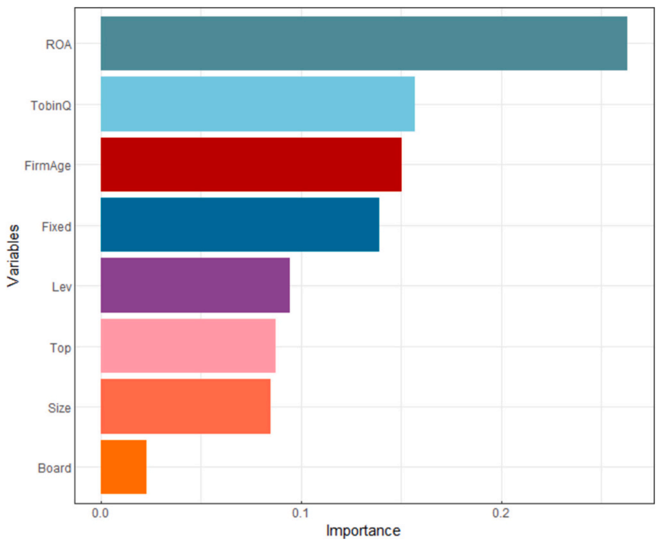

Fig. 9. Variable importance plot.
Note: The horizontal axis represents the importance scores for each variable, and the vertical axis represents the variable names.

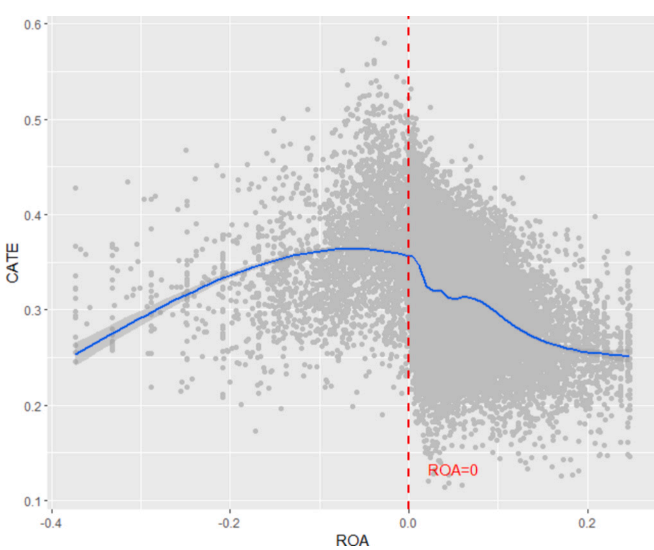

Fig. 10. Variance in policy effects generated by the AIPZ policy with changes in ROA.
Note: The red vertical dashed line represents ROA = 0. Conditional average treatment effect (CATE) represents the policy effects under different ROA conditions.

attributed to several causes. First, when ROA is negative, firms may be experiencing operational difficulties or instability, facing greater pressure to reduce costs and optimize resource efficiency. In such circumstances, firms might be more motivated to adopt AI technologies, considering them to be crucial for reversing operational downturns and enhancing market competitiveness. Additionally, the initiation of AIPZ programs could attract more attention to these firms, helping alleviate investor and market concerns about their operational status. Therefore, firms with negative ROA might actively respond to policy initiatives, striving to improve their corporate image through concrete actions and ultimately achieving a fundamental turnaround in operations. Conversely, firms with positive ROA are likely to be in relatively good operational condition, with stable or growing profits. Such firms might prefer maintaining the status quo and could be cautious about incurring additional environmental costs, particularly if the introduction and upgrading of AI technologies lead to short-term increases in production costs. As a result, the impact of AI on improving carbon performance might be more limited for firms with positive ROA.

6.3.2. Heterogeneity based on Tobin's Q

Fig. 11 illustrates the relationship between the treatment effect and the Tobin's Q (*TobinQ*) heterogeneity factor. The results reveal an interesting trend in which, when Tobin's Q is less than 1, the treatment effect rises rapidly, remains at a peak between 1 and 2, and finally, when Tobin's Q exceeds 2, the treatment effect gradually declines. Notably, the treatment effect exhibits a slow rebound when Tobin's Q is greater than 10, but this is not further examined due to the small sample size.

To explain this trend, it is essential to understand the meaning of Tobin's Q, which is the ratio of a firm's market value to its asset replacement cost. The market value of a firm's stock represents investors' assessment, while the asset replacement cost theoretically represents the firm's fundamental value. Therefore, when Tobin's Q is less than 1, it indicates that the market undervalues the firm, suggesting market caution concerning the firm's prospects or inefficient asset allocation. Conversely, when Tobin's Q is greater than 1, it indicates that the market overvalues the firm, generally reflecting a positive assessment, as this indicates that investors believe the firm's assets can generate higher value than alternative investments.

Considering the meaning of Tobin's Q, we revisit Fig. 11. When Tobin's Q is between 1 and 2, the firm's market value roughly equals its replacement cost, meaning the market valuation accurately reflects the firm's fundamental value, and the treatment effect remains at its peak. When Tobin's Q is less than 1, the market undervalues the firm's fundamental value, resulting in a relatively lower treatment effect; however, as Tobin's Q approaches 1, the treatment effect rapidly rises to its peak. When Tobin's Q exceeds 2, the market significantly overvalues the firm's fundamental value, causing the treatment effect to gradually decline. This indicates that the policy treatment effect is stronger when the firm's fundamental value is accurately estimated by the market. This could be because the policy can better align with market expectations and the firm's actual performance, thereby generating a more significant impact.

Specifically, when Tobin's Q is between 1 and 2, the firm's market and fundamental value are aligned, making it easier for firms to benefit from AI policies. In this balanced state, the market and the firm itself can more accurately understand and leverage the advantages brought by AI

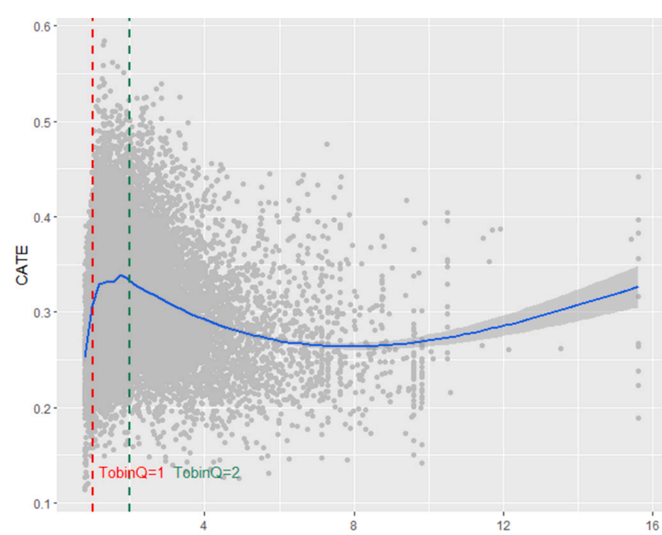

Fig. 11. Variance in policy effects of the AIPZ policy with changes in Tobin's Q.
Note: The red vertical dashed line represents Tobin's Q = 1, and the green vertical dashed line represents Tobin's Q = 2. Conditional average treatment effect (CATE) represents the policy effects under different Tobin's Q conditions.

technology. AI can optimize resource allocation, enhance production efficiency, and reduce costs, which is particularly significant for firms in this balanced state. When Tobin's Q is less than 1, the market undervalues the firm's worth, indicating that these firms may face operational challenges and resource constraints. In such cases, implementing AI policies can help these firms improve operational efficiency, reduce costs, and enhance market performance. Therefore, as Tobin's Q approaches 1, firms can better leverage AI technology to enhance their value, leading to a rapid increase in the treatment effect to its peak. When Tobin's Q exceeds 2, the market overestimates the firm's fundamental value, and these firms may already have high profitability and market recognition. However, the potential short-term cost increases associated with further AI technology improvement might make these firms hesitant to invest. Consequently, the treatment effect gradually declines as Tobin's Q rises. Nevertheless, such firms still have certain advantages in technological leadership and market position, and the decline in the treatment effect is relatively slow.

Moreover, from the perspective of AIPZ city governments, extensive market research and enterprise needs assessments are typically conducted when promoting AI policies to ensure that policies effectively meet firms' actual conditions. Therefore, when a firm's actual situation is accurately reflected, policy specifics are more likely to align with its actual needs, subsequently increasing the treatment effect.

7. Conclusions and policy implications

This study uses data from Chinese listed companies from 2013 to 2022 and considers the AIPZ policy as a quasi-natural experiment to explore its impact on firms' carbon performance. In the mechanism analysis, this study considers the moderating effects of talent, media sentiment, internal control, and firm pollution level. The study also employs machine learning techniques in heterogeneity analysis to more precisely and intuitively assess the impact of heterogeneity factors on the treatment effect.

The main conclusions of this study are as follows. First, the AIPZ policy has a significant positive impact on firm carbon performance; a conclusion that holds under a series of robustness tests. This finding enriches the existing literature on the relationship between technological innovation and firms' environmental performance, particularly in the context of AI application in environmental management. The mechanism analysis reveals that firms with higher talent levels, more positive media sentiment, and better internal control experience more pronounced carbon performance improvement due to the AIPZ policy. This indicates that firms with high-quality talent can more effectively leverage AI technology for carbon reduction, positive media coverage can boost firms' confidence in the policy and promote the application of AI technology in carbon reduction, and good internal control can ensure the effective implementation and operation of AI technology. Additionally, the treatment effect is relatively smaller for heavily-polluting firms compared to non-heavily polluting firms, indicating that heavily-polluting firms face greater challenges in using AI technology for carbon reduction. The heterogeneity analysis reveals the importance of ROA and Tobin's Q in heterogeneity through variable importance analysis using GRF. When ROA is negative, the policy effect is large and shows a slow upward trend, and when ROA is positive, the policy effect quickly declines, showing a clear zero-boundary effect. The relationship between Tobin's Q and the policy effect presents an inverted U-shape, with the largest policy effect when Tobin's Q is between 1 and 2.

Based on these conclusions, this study proposes the following policy recommendations to enhance the effectiveness of AI policies in improving firm carbon performance. First, local governments should vigorously promote firms' application of AI technology to improve carbon performance. Specifically, special funds can be established to support firms' AI research and application, particularly for the development of technologies for carbon emissions monitoring, management, and optimization. In addition, tax breaks and financial subsidies can be used to encourage firms to invest in relevant AI technologies to improve efficiency and effectiveness in carbon reduction. Governments can also organize regular training sessions and seminars to introduce firms to the latest developments in AI technology and application examples to enhance AI technological capabilities and management.

Second, governments should support firms in cultivating and introducing high-quality talent, particularly those with expertise in AI and environmental management. This can be achieved through special funding, scholarships, training programs, and promoting international talent exchanges. Firms should also provide internal training to enhance existing employees' skills to make them better equipped to use AI technology for carbon reduction.

Additionally, governments and firms should strengthen cooperation with the media to actively publicize environmentally friendly firms and successful carbon reduction cases. Environmental awards or environmental protection campaigns can be established to increase public awareness and positive attitudes toward environmental issues. Positive media coverage can enhance the confidence of firms and the public concerning in the role of AI in environmental protection to foster a favorable public opinion environment and promote the application of AI technology in carbon reduction.

Moreover, governments should formulate relevant regulations to encourage firms to strengthen internal control to ensure the effective implementation of AI technology in carbon management. Internal control guidelines can be developed, internal control assessments can be conducted, and firms that excel in internal control can be rewarded. Firms should establish sound internal control systems to ensure the effective application and continuous improvement of AI technology, which will enhance their carbon performance.

Governments should provide more technical support and financial subsidies to help heavily polluting firms overcome the difficulties of technological transformation. Special funds can be established to support the introduction and application of advanced AI technology in heavily polluting firms, and tax breaks and low-interest loans can be provided to reduce transformation costs. Governments should also strengthen heavily polluting firms' supervision to ensure that they continue to improve their technical levels and management capabilities while achieving carbon reduction goals to advance sustainable development.

Compared with previous research, this study reveals the actual impact of AI on firm carbon performance from the perspective of AIPZ policy implementation, enriching the literature on the relationship between AI and environmental performance. The mechanism analysis considers the moderating effects of talent, media sentiment, internal control, and firm pollution level, systematically analyzing how these factors influence the impact of AI on carbon performance, which fills the gap in mechanism research in the existing literature. Furthermore, unlike traditional heterogeneity analysis methods such as grouped regression, this study innovatively employs machine learning methods in heterogeneity analysis, providing a more detailed and intuitive evaluation method that further enhances the rigor and credibility of the research.

Despite the progress made in this study, some research gaps remain. Future research can explore other potential mechanisms such as the impact of corporate culture and the external market environment on the effectiveness of AI policies, and conduct cross-country comparative studies to understand the policy implementation effects of similar initiatives in different countries and regions. Additionally, existing research lacks comparisons between different types of firms. Therefore, future research can further explore the differentiated performance and underlying logic of firms of different sizes and industry backgrounds in adopting AI technology and optimizing carbon performance to provide a scientific basis for firms to develop more targeted AI application strategies, jointly promoting the green, low-carbon, and high-quality development of the global economy.

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CRediT authorship contribution statement

Lingbing Feng: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Jiajun Qi:** Writing – original draft, Data curation, Conceptualization. **Yuhao Zheng:** Visualization, Investigation.

Appendix A. Correlation analysis

Table A1
Results of variable correlation analysis.

	Carbon	did	Size	Lev	ROA	Board	Top	TobinQ	FirmAge	Fixed
Carbon	1									
AIPZ	0.239***	1								
Size	0.047***	0.081***	1							
Lev	0.017**	0.021***	0.526***	1						
ROA	−0.030***	−0.030***	0.00300	−0.372***	1					
Board	−0.046***	−0.055***	0.278***	0.157***	−0.00300	1				
Top	−0.052***	−0.00600	0.204***	0.044***	0.133***	0.014**	1			
TobinQ	−0.047***	0.00500	−0.373***	−0.290***	0.209***	−0.122***	−0.097***	1		
FirmAge	0.172***	0.133***	0.160***	0.143***	−0.070***	0.069***	−0.072***	−0.055***	1	
Fixed	−0.041***	−0.160***	0.092***	0.054***	−0.073***	0.141***	0.079***	−0.095***	−0.00500	1

Note: *, **, and *** indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively. Overall, most of the coefficients are statistically significantly correlated, which support us for further analysis in this study.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.108040.

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