

## Article

# Climate Policy Uncertainty and Corporate Industrial Intelligence: A Socio-Technical Systems Perspective on Board Governance

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## Abstract

Frequent introductions and revisions of climate policy instruments constitute a salient exogenous shock to firms' strategic decisions. From a socio-technical systems perspective, climate policy uncertainty (CPU) represents an external institutional disturbance that reshapes the interaction between firms' technological upgrading and organizational governance. Using panel data on 1783 Chinese listed firms from 2011–2024, we examined how CPU affects firms' industrial intelligence. We employed fixed-effects models, mediation, and moderation analyses, supplemented by robustness tests. We found that, first, CPU significantly promotes firms' industrial intelligence transformation. Second, board governance plays a key moderating role: higher board educational attainment, stronger innovation orientation, and an environmental or risk committee significantly strengthen CPU's positive effect on industrial intelligence. Third, CPU promotes industrial intelligence mainly through two channels: an opportunity effect via increased R&D investment, and a pressure effect via reduced total factor productivity, pushing firms to adopt intelligent transformation to address productivity pressure. Moreover, this effect is stronger for firms in high-pollution industries, larger firms, and long-established firms. These findings suggest that corporate industrial intelligence is not merely a technological response, but a socio-technical adaptation process shaped by climate policy uncertainty, board governance, and resource reconfiguration. This study provides evidence on firms' digital, intelligent, and green transformation under climate policy uncertainty and offers implications for board governance and sustainable adaptation.

**Keywords:** socio-technical systems perspective; corporate industrial intelligence; climate policy uncertainty; board governance; dynamic capability theory



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## 1. Introduction

As global climate change becomes increasingly severe, governments around the world have frequently introduced targeted climate policies, giving rise to climate policy uncertainty [1–3]. This climate policy uncertainty (CPU) is profoundly reshaping firms' strategic choices and has become a central concern in boards' risk governance [4,5]. Climate policy uncertainty not only exerts pressure on firms to undertake structural transformation, but also creates new opportunities for technological innovation and green upgrading [6,7]. Against this backdrop, corporate industrial intelligence (II) has emerged as a key driver of the new wave of technological and industrial transformation. It not only improves

production efficiency, optimizes factor allocation, and reduces carbon emissions, but also constitutes an important strategic option for firms seeking to enhance resilience and competitiveness in an uncertain environment [8,9].

From a socio-technical systems perspective, firms can be viewed as adaptive systems embedded in broader institutional, technological, and market environments [10,11]. Climate policy uncertainty represents an external institutional disturbance, while corporate industrial intelligence reflects a technological response through which firms enhance automation, flexibility, and adaptive capacity. Board governance connects these two domains by interpreting policy signals and guiding strategic resource allocation. Accordingly, the relationship between climate policy uncertainty and corporate industrial intelligence is not merely a policy–technology link, but a socio-technical adaptation process involving institutional pressure, technological upgrading, and governance coordination.

As the largest developing economy and a major emitter of greenhouse gases, China has introduced a series of climate and environmental policies to fulfill its international commitments. These policies include, for example, green finance policies, emission reduction policies for key industries, and carbon market trading schemes [12–14]. While these policies have effectively promoted green and low-carbon development, the dynamic adjustments in policy standards and subsidy intensity have also generated significant climate policy uncertainty [15,16]. Furthermore, China’s traditional industries, such as manufacturing, are of enormous scale, meaning that Chinese firms face more urgent transformation pressures when adapting to evolving climate policies. Therefore, Chinese firms have a greater need to take measures to address such climate policy risks [17–19]. This context also provides a representative setting for examining how CPU affects firms’ industrial intelligence transformation and how board governance shapes this relationship. China provides a suitable setting for this socio-technical inquiry because frequent climate policy adjustments coexist with rapid industrial digitalization, large-scale manufacturing transformation, and heterogeneous corporate governance structures.

Industrial intelligence has emerged as a core engine of the new wave of industrial transformation. It is often manifested in firms’ large-scale adoption of industrial robots, which enables the automation and intelligentization of manufacturing processes [20,21]. Existing research suggests that firms’ industrial intelligence is shaped by both internal and external factors. Internally, firm size, the severity of financing constraints, R&D investment, and labor costs influence firms’ decisions to advance industrial intelligence [22]. Externally, industrial policy, market competition, the institutional environment, and regulatory pressure shape firms’ adoption and investment in industrial robots, thereby accelerating industrial intelligence transformation [23,24]. In this study, corporate industrial intelligence is not treated as a narrow technological input, but as a firm-level technological subsystem that reflects automation-oriented and intelligent manufacturing transformation.

As the core body for strategic decision-making, the board of directors’ risk governance capability largely determines firms’ responsiveness to external policy shocks and their operating performance. Prior research suggests that board structure, including board size, CEO duality, and the establishment of specialized committees, shapes firms’ monitoring intensity and internal checks and balances, thereby affecting the rigor and coherence of corporate strategy formulation [25,26]. On the other hand, director attributes such as gender, age, educational attainment, and technical expertise influence firms’ information processing capacity and decision quality, thereby shaping strategic choices [27–29]. Therefore, amid heightened volatility in climate policy and rising transformation pressures, it is theoretically and practically important to examine how boards help firms respond to climate policy uncertainty and undertake industrial intelligence transformation. Within a socio-technical system, board governance functions as a key organizational governance subsystem that

links external institutional uncertainty with internal technological transformation by processing climate-policy information, evaluating strategic risks, and coordinating resource allocation. In this study, the socio-technical system consists of four interrelated components: climate policy uncertainty as the external institutional disturbance, board governance as the organizational governance subsystem, R&D investment and productivity pressure as resource reconfiguration mechanisms, and corporate industrial intelligence as the technological adaptation outcome.

Existing studies have examined climate policy uncertainty and environmental regulation, digital transformation and industrial intelligence, and board governance, respectively. However, these streams of research have largely developed in parallel. Less attention has been paid to how external climate-policy uncertainty, internal governance, resource reconfiguration, and production-side intelligent transformation interact within a unified firm-level system. This gap is important because corporate industrial intelligence is not merely a technological investment decision or a direct response to environmental regulation, but a socio-technical adaptation process shaped by policy pressure, governance coordination, and technological adjustment.

Based on the above analysis, we used panel data of 1783 Chinese listed firms from 2011 to 2024 to examine the impact of CPU on firms' industrial intelligence and its underlying mechanisms and further investigate the moderating role of board governance. The empirical results show that, first, CPU significantly promotes firms' industrial intelligence transformation, and this finding remains robust after a series of robustness checks. Second, board governance plays a crucial moderating role: boards with higher educational attainment, stronger innovation orientation, and the presence of an environmental and risk committee can significantly reinforce the positive effect of CPU on industrial intelligence. Third, this positive effect is primarily transmitted through two channels: the "opportunity effect" and the "pressure effect". On the one hand, CPU increases firms' R&D investment, prompting them to proactively undertake industrial intelligence transformation. On the other hand, CPU depresses firms' TFP, thereby generating a pressure effect that pushes firms to alleviate difficulties through industrial intelligence transformation. Furthermore, the positive effect of CPU on industrial intelligence is significantly stronger for firms in high-pollution industries, large-scale firms, and long-established firms.

Our contributions are threefold. First, we clarify the theoretical novelty of framing corporate industrial intelligence as a socio-technical adaptation process. Prior studies mainly examine firms' responses to climate policy uncertainty in terms of investment, financing, green innovation, or digital transformation, while research on industrial intelligence often treats technological upgrading as a technology-adoption outcome. We extend these studies by showing how external institutional pressure, board-level governance, resource reconfiguration, and technological adjustment jointly shape firms' intelligent transformation.

Second, we extend the literature on corporate industrial intelligence by identifying two resource-reconfiguration mechanisms through which CPU promotes intelligent transformation: an opportunity-driven channel via increased R&D investment and a pressure-driven channel via reduced TFP. This reveals how firms adjust internal resources and production systems under climate-policy uncertainty.

Third, we enrich research on board governance under policy uncertainty by showing that board educational attainment, board innovation orientation, and environmental or risk committees strengthen the positive effect of CPU on corporate industrial intelligence. This highlights board governance as a key condition that helps firms translate external climate-policy uncertainty into internal technological transformation.

The rest of this study is organized as follows. Section 2 presents the theoretical analysis and hypotheses. Section 3 describes the research design. Section 4 reports the empirical

results. Section 5 discusses the findings and limitations. Section 6 concludes the study and presents the implications.

## 2. Theoretical Analysis and Hypotheses

### 2.1. *Climate Policy Uncertainty and Corporate Industrial Intelligence: A Socio-Technical Systems Perspective*

Socio-technical systems theory provides an overarching theoretical basis for understanding the relationship between climate policy uncertainty and corporate industrial intelligence. It emphasizes that organizational transformation depends on the alignment and joint optimization of social and technical subsystems rather than on technological change alone [30,31]. In the context of this study, climate policy uncertainty increases uncertainty about future regulatory requirements, compliance costs, and low-carbon transition opportunities, creating pressure for firms to reconfigure their production systems. Corporate industrial intelligence constitutes this technological reconfiguration by improving production efficiency, operational flexibility, and resilience, while board governance strengthens the social and organizational capacity to evaluate risks, process external information, and support resource allocation. Therefore, under climate policy uncertainty, corporate industrial intelligence can be understood as a system-level adaptive outcome shaped by external institutional pressure, governance mechanisms, and technological upgrading.

From this perspective, the relationship between climate policy uncertainty and corporate industrial intelligence reflects a dynamic interaction among institutional, governance, resource, and technological subsystems. Climate policy uncertainty changes firms' expectations about future regulation and transition costs; board governance interprets these external signals and coordinates strategic responses; R&D investment and productivity pressure transmit external uncertainty into internal resource reconfiguration; and corporate industrial intelligence represents the resulting technological adaptation. Therefore, this process should be understood not as a simple policy–technology relationship, but as a socio-technical adaptation process shaped by subsystem interactions.

Based on dynamic capability theory, firms can sustain competitive advantage in highly uncertain environments by strengthening their ability to sense external changes, seize opportunities, and adjust strategies [32–34]. Prior research shows that when firms face policy uncertainty, those that invest earlier in high-technology domains are more likely to maintain stronger performance [35,36]. When CPU rises, regulatory standards and incentive schemes become more complex and volatile. Firms that continue to rely on energy-intensive and high-emission production modes are more likely to be caught unprepared when regulation tightens [37,38]. As part of corporate industrial intelligence, firms can more readily capture policy benefits related to low-carbon transition while improving operational efficiency [39,40]. Therefore, corporate industrial intelligence can strengthen firms' adaptability and responsiveness to climate policy changes, thereby enhancing their dynamic capabilities.

Meanwhile, dynamic capability theory emphasizes that under uncertainty, firms cannot defend against risks solely through short-term cost cutting, but instead need forward-looking investments to integrate internal and external resources. This helps strengthen core capabilities and environmental resilience [41,42]. CPU increases the costs and risks of traditional development models [43,44]. At the same time, it raises the medium- to long-term returns to high-technology solutions such as smart manufacturing [45]. In this context, placing corporate industrial intelligence into firms' long-term strategies can improve resource allocation efficiency and strengthen operational resilience under policy uncertainty. Therefore, climate policy uncertainty is expected to promote corporate in-

dustrial intelligence by encouraging firms to reconfigure their technological systems in response to external institutional change.

**H1.** *Climate policy uncertainty promotes corporate industrial intelligence.*

## 2.2. Mediating Mechanisms Between Climate Policy Uncertainty and Corporate Industrial Intelligence

From a socio-technical systems perspective, firms respond to external institutional disturbances through both proactive capability building and pressure-driven system adjustment. Climate policy uncertainty may not only create opportunities for firms to invest in intelligent technologies, but also expose the inefficiency of existing production systems. Accordingly, this study identifies two mediating mechanisms: an opportunity effect through R&D investment and a pressure effect through total factor productivity.

According to real options theory, when the future environment is uncertain, firms' R&D investment is not merely a current cost but also a forward-looking "technology option" investment [46,47]. Prior research has found that as environmental regulation intensifies, the risks and costs of continuing to rely on energy-intensive and high-emission technologies rise significantly [48]. By increasing R&D investment, firms can capture potential policy benefits and build technological capabilities to respond to policy changes. In the socio-technical adaptation process, R&D investment reflects an opportunity-driven capability-building pathway through which firms strengthen their technological subsystem and improve their readiness for intelligent transformation. Such option-value driven R&D decisions generate an "opportunity effect", which in turn promotes firms' industrial intelligence.

The Porter hypothesis posits that well-designed environmental regulation can enhance firms' long-run competitiveness through innovation compensation [49,50]. Regulatory pressure induced by CPU may raise compliance costs in the short run and reduce total factor productivity (TFP). This pressure effect can expose inefficiencies in traditional production models and trigger problematic search for efficiency-enhancing technological and organizational solutions [51–53]. From a socio-technical systems perspective, reduced TFP indicates that existing production systems face efficiency pressure under climate policy uncertainty. Industrial intelligence may help alleviate such pressure by improving production efficiency, reducing operating costs, and enhancing operational flexibility [38].

However, reduced TFP does not automatically lead to technological upgrading, as it may also reflect weaker capabilities or resource constraints. Therefore, we interpret TFP decline as a pressure-induced adaptation mechanism under climate policy uncertainty rather than as a mechanical effect through which all low-productivity firms pursue industrial intelligence. Thus, the pressure effect reflects a system-adjustment pathway through which firms may adopt corporate industrial intelligence to restore efficiency and enhance adaptive capacity.

**H2a (Opportunity Effect).** *Climate policy uncertainty promotes corporate industrial intelligence by increasing firms' R&D investment.*

**H2b (Pressure Effect).** *Climate policy uncertainty promotes corporate industrial intelligence by reducing firms' total factor productivity.*

## 2.3. The Moderating Role of Board-Level Risk Governance

From a socio-technical systems perspective, board governance functions as a key organizational governance subsystem that links external institutional uncertainty with internal technological transformation. Organizational information processing theory argues that external environmental uncertainty substantially increases managers' demand for

information processing capacity [54]. Under high climate policy uncertainty, corporate governance requires continuous attention to ongoing adjustments in climate policy. As a key hub linking the external policy environment with internal resource allocation, the board's personnel characteristics and governance structure directly affect whether firms can translate CPU into forward-looking strategic actions [28,55,56]. Rather than measuring narrowly defined climate-specific governance capacity, these board governance variables capture broader board-level capabilities that become particularly relevant when firms respond to climate policy uncertainty.

It should also be noted that climate policy uncertainty may induce a “wait-and-see” attitude among managers. When future regulatory standards, subsidies, or compliance requirements remain unclear, managers may delay irreversible investments in production processes that are closely related to government policies. This cautious response may weaken or postpone firms' industrial intelligence transformation. However, from a socio-technical systems perspective, this potential delaying effect is not uniform across firms. Boards with stronger information-processing capacity and risk governance capability can better interpret climate policy signals, assess long-term regulatory trends, and reduce managerial hesitation. Therefore, board-level risk governance may help firms transform climate policy uncertainty from a source of passive waiting into a trigger for proactive technological adaptation.

The literature suggests that boards with higher average educational attainment are better able to interpret complex policy texts and absorb new knowledge [29,57]. Higher board educational attainment can strengthen the information-processing capacity of the governance subsystem, helping firms understand the institutional logic and direction underlying CPU. Therefore, boards with higher average educational attainment are more likely to understand the institutional logic and direction underlying CPU and to form sound judgments under incomplete information. As CPU rises, they are thus more inclined to incorporate industrial intelligence into corporate strategy, thereby strengthening the positive effect of CPU on corporate industrial intelligence.

Building on this, the board's innovation orientation also shapes how it responds to CPU. From an organizational information processing perspective, boards with a stronger innovation orientation are more willing to increase technology and R&D investment in industrial intelligence to respond to climate policy uncertainty [58]. From a socio-technical systems perspective, innovation-oriented boards strengthen the coupling between the governance subsystem and the technological subsystem by reallocating resources toward intelligent manufacturing and technological upgrading. This, in turn, strengthens the positive effect of CPU on corporate industrial intelligence.

Organizational information processing theory (OIPT) also emphasizes that formal organizational structures can improve the depth and efficiency of information processing [59,60]. A dedicated environmental and risk committee provides a specialized platform for the board to systematically identify, assess, and monitor CPU-related risks, and to embed these assessments into major investments and strategic planning [61,62]. Such a committee institutionalizes the connection between external climate policy signals and internal technological transformation. Compared with firms without such a committee, firms that establish or strengthen an environmental and risk committee are better able to translate CPU into strategic decisions and to treat industrial intelligence as a core tool for coping with policy uncertainty. As a result, they amplify the positive effect of CPU on corporate industrial intelligence.

**H3a.** *The positive effect of climate policy uncertainty on corporate industrial intelligence is positively moderated by the board's average educational attainment.*

**H3b.** The positive effect of climate policy uncertainty on corporate industrial intelligence is positively moderated by the board's innovation orientation.

**H3c.** The positive effect of climate policy uncertainty on corporate industrial intelligence is positively moderated by the presence of dedicated environmental and risk committees.

The conceptual framework of this study is illustrated in Figure 1.

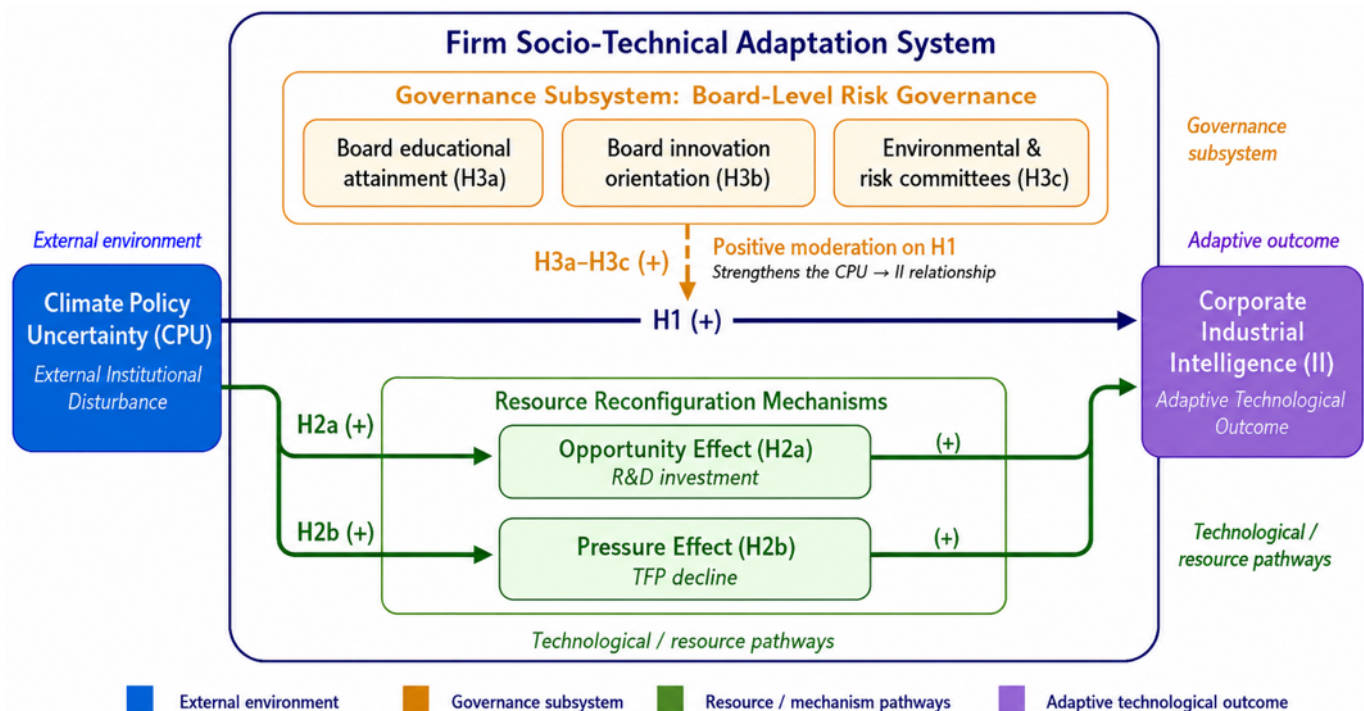


Figure 1. The conceptual framework.

### 3. Research Design

#### 3.1. Variable Measurement

##### 3.1.1. Industrial Intelligence

Conceptually, corporate industrial intelligence refers to the firm-level transformation of production systems toward intelligent, adaptive, and data-enabled manufacturing. It is related to, but distinct from, simple automation, digitalization, and capital deepening. While automation mainly emphasizes the replacement of manual tasks by machines, industrial intelligence further emphasizes programmable control, adaptive production, and the integration of physical production equipment with information and control systems. Digitalization is broader and may involve non-production activities, whereas capital deepening reflects a general increase in capital intensity and does not necessarily imply intelligent production capabilities.

Empirically, because it is difficult to observe all dimensions of Industry 4.0 transformation at the firm-year level, we use industrial robot penetration as a proxy for the embodied and production-side dimension of corporate industrial intelligence, following current research [22]. Industrial robots are closely related to intelligent manufacturing because they combine programmable control, precision execution, flexible task adjustment, and production-process upgrading. This proxy is also relevant to climate policy uncertainty: when firms face uncertain future regulatory standards, compliance costs, energy-efficiency requirements, and low-carbon transition incentives, they may adopt robots and related intelligent equipment to improve production efficiency, flexibility, and

adaptability. Therefore, our measure should be interpreted as a robot-based proxy for the production-side dimension of corporate industrial intelligence rather than a complete measure of all dimensions of industrial intelligence.

We constructed a corporate industrial intelligence (II) measure based on industrial robot penetration using a shift-share Bartik approach. First, we constructed the industry-level penetration rate of industrial robots in China according to Equation (1):

$$II_{m,t} = \frac{ROBOT_{m,t}}{L_{m,t=2010}} \quad (1)$$

where  $II_{m,t}$  denotes the penetration rate of industrial robots in industry  $m$  in year  $t$ ;  $ROBOT_{m,t}$  represents the stock of industrial robots in  $m$  industry in  $t$  year in China;  $L_{m,t=2010}$  represents the employment in 2010 (base period) in  $m$  industry in China. We used 2010 as the base year to fix the employment denominator at the pre-period level and to mitigate concerns about endogenous adjustments in industry employment.

Second, we constructed the corporate penetration rate of industrial robots according to Equations (2) and (3):

$$\omega_{i,m} = \frac{R.S_{i,m,t=2011}}{\bar{R.S}_{m,t=2011}} \quad (2)$$

$$II_{i,t} = \omega_{i,m} \times II_{m,t} \quad (3)$$

where  $II_{i,t}$  represents firm  $i$ 's exposure to industrial robot penetration in year  $t$ .  $\omega_{i,m}$  is a time-invariant corporate exposure weight that captures firm  $i$ 's baseline intensity of production activities within industry  $m$ . Since detailed workforce composition data for listed firms in China are available from 2011 onward,  $R.S_{i,m,2011}$  denotes firm  $i$ 's share of employees in production-related positions in 2011 (base year) within industry  $m$ , and  $\bar{R.S}_{m,2011}$  denotes the industry- $m$  median of the same measure in 2011. The ratio serves as the baseline exposure weight, which is interacted with the time-varying industry-level penetration  $II_{m,t}$  to obtain the firm-year II measure.

### 3.1.2. Climate Policy Uncertainty

We measured climate policy uncertainty using the city-level Chinese Climate Policy Uncertainty (CCPU) index developed by Ma et al. (2023) [63]. This index is constructed from climate-policy-related news texts in six major Chinese newspapers using a MacBERT-based deep learning classifier, following the news-based uncertainty measurement framework of Baker et al. (2016) [32]. The index captures the intensity of uncertainty surrounding climate-policy discussions by identifying and standardizing the frequency of news articles related to climate policy uncertainty. The CCPU dataset provides national-, provincial-, and city-level indices, allowing researchers to examine climate policy uncertainty at different geographic levels.

In this study, we used the annual city-level CCPU index for 293 prefecture-level cities in China. The city-level index is appropriate because firms are affected not only by national climate policy signals, but also by local policy implementation, regulatory enforcement, and regional climate-policy discussions. We matched each firm-year observation to the city where the firm is registered, so the CPU variable varied across both cities and years. We used annual city-level CPU data from 2010 to 2023 and employed the one-year lag of CPU in the regression analysis to ensure that climate policy uncertainty was measured prior to firms' industrial-intelligence outcomes and to mitigate potential simultaneity concerns. Since the city-level CPU index is available through 2023, using L.CPU allows our sample period to extend to 2024.

### 3.1.3. Mediating Variables

To unpack the channels through which climate policy uncertainty affects corporate industrial intelligence, we focused on two mediators: firms' R&D investment and total factor productivity.

**R&D investment (*R&D*).** Following the standard practice in the innovation and corporate finance literature, we proxied firms' innovation input by annual R&D expenditure and applied a logarithmic transformation to mitigate right-skewness and reduce the influence of outliers. Specifically, we used the natural logarithm of R&D spending, measured as  $\ln(1 + \text{R\&D})$ . Because project-level climate-related R&D expenditure is generally not separately disclosed, this measure captures firms' overall innovation input rather than the exact share of R&D devoted to climate-policy initiatives.

**R&D intensity (*RD\_Intensity*).** To further capture firms' relative innovation input, we used R&D intensity as an alternative measure of the innovation-input channel. *RD\_Intensity* is measured as firm R&D expenditure divided by total assets. Compared with the logarithm of R&D expenditure, this measure accounts for differences in firm scale and reflects the intensity of innovation input relative to firms' asset base.

**Total factor productivity (*TFP*).** Firm productivity is measured by total factor productivity estimated using the Levinsohn–Petrin (LP) approach [64]. The LP approach uses intermediate inputs to control for unobserved productivity shocks and mitigate simultaneity bias in production-function estimation. Compared with ordinary least squares estimation, the LP approach helps reduce bias arising from the endogenous adjustment of firms' input choices in response to productivity changes. The firm-level LP-TFP data were obtained from the China Stock Market and Accounting Research Database (CSMAR).

### 3.1.4. Board-Level Risk Governance Variables

To test the moderating role of board-level risk governance, we constructed four variables capturing board human capital, strategic orientation, and formal committee structures. The following variables were intended to capture board-level governance capabilities relevant to firms' responses to climate policy uncertainty, rather than direct measures of narrowly defined climate-specific governance capacity.

**Board educational attainment (*Board\_Edu*).** We measured board human capital by the board's average educational attainment. Specifically, we converted each director's highest education level into years of schooling and computed the board-level average years of education in year  $t$  [57]. To improve comparability across specifications, we normalized the measure to the  $[0, 1]$  interval using min–max scaling in Equation (4):

$$\text{Board\_Edu}_{i,t}^{\text{norm}} = \frac{\text{Board\_Edu}_{i,t} - \min(\text{Board\_Edu})}{\max(\text{Board\_Edu}) - \min(\text{Board\_Edu})} \quad (4)$$

**Board STEM background (*Board\_STEM*).** To further capture the technical relevance of board human capital, we measured the proportion of board directors with STEM educational backgrounds. Specifically, *Board\_STEM* is calculated as the number of board directors with educational backgrounds in science, technology, engineering, or mathematics divided by the total number of board directors.

**Board innovation orientation (*Board\_Innov*).** We measured the board's innovation orientation using a text-based indicator from the board report section of firms' annual reports. Specifically, we counted the frequency of innovation-related terms, such as innovation, R&D, technological upgrading, intelligent manufacturing, digitalization, and automation, and divided it by the total word count of the board report to control for report length [21,51]. The resulting measure was then min–max normalized to the  $[0, 1]$  interval. A higher value indicates stronger board-level attention to innovation.

Environmental or risk committee (*Board\_EnvRiskComm*). We constructed a dummy variable capturing whether the firm had established a dedicated environmental committee or risk committee at the board level. *Board\_EnvRiskComm* equals 1 if either committee exists in year  $t$ , and 0 otherwise. This indicator reflects formal board structures that strengthen monitoring and risk oversight and facilitate the integration of risk considerations into strategic decisions [65,66]. However, due to data limitations, this binary indicator captures only the formal existence of an environmental or risk committee, rather than its actual activity, meeting frequency, member expertise, or influence on board decisions.

### 3.1.5. Control Variables

Following the extant literature, we controlled for a series of variables that may affect corporate industrial intelligence. Firm-level control variables include firm age (*Age*), firm size (*Size*), cash ratio (*Cash*), leverage (*Lev*), profitability (*RoA*), return on equity (*RoE*), audit quality (*Audit*), share of top 10 shareholders (*Top10*), and CEO-chair separation (*Separation*). To account for regional economic conditions, we further included the natural logarithm of the gross domestic product of the city where the firm is registered (*Ingdp*). This city-level variable was used to control for differences in local economic development, infrastructure, market demand, and resource availability, which may be correlated with both climate policy uncertainty and firms' industrial intelligence transformation.

Detailed definitions of all control variables are provided in Appendix A.1.

## 3.2. Regression Model Specification

### 3.2.1. Baseline Model

To examine the impact of climate policy uncertainty on corporate industrial intelligence, we estimated Equation (5):

$$II_{i,t} = \alpha + \beta_1 CPU_{c,t-1} + \gamma' Controls_{i,c,t} + \mu_i + \lambda_t + \varepsilon_{i,c,t} \quad (5)$$

Here,  $i$  indexes firms and  $t$  indexes years, and  $c$  denotes the city where firm  $i$  is located. The dependent variable  $II_{i,t}$  measures firm  $i$ 's industrial intelligence in year  $t$  (Section 3.1.1). We used the one-year lag of CPU to mitigate potential simultaneity and reverse-causality concerns and ensure that CPU was measured prior to the firms' industrial-intelligence outcomes. The key explanatory variable  $CPU_{c,t-1}$  was the city-level climate policy uncertainty index in year  $t - 1$  (Section 3.1.2).  $Controls_{i,c,t}$  included corporate controls and city-level macro controls. We included firm fixed effects  $\mu_i$  and year fixed effects  $\lambda_t$ .  $\varepsilon_{i,c,t}$  is the error term, and standard errors are robust and clustered at the firm level. The coefficient of interest is  $\beta_1$ , and H1 predicts  $\beta_1 > 0$ .

### 3.2.2. Mediation Models

To test the mediating mechanisms, we estimated the following Equations (6) and (7):

$$M_{i,t} = \alpha + \delta_1 CPU_{c,t-1} + \theta' Controls_{i,c,t} + \mu_i + \lambda_t + \varepsilon_{i,c,t} \quad (6)$$

$$II_{i,t} = \alpha + \phi_1 M_{i,t} + \phi_2 CPU_{c,t-1} + \kappa' Controls_{i,c,t} + \mu_i + \lambda_t + \varepsilon_{i,c,t} \quad (7)$$

$M_{i,t}$  denotes the mediator. For the opportunity effect (H2a), we set  $M_{i,t} = R\&D_{i,t}$ . We expected  $\phi_1 > 0$  and  $\phi_2 > 0$ , indicating that CPU increases R&D investment and higher R&D promotes industrial intelligence. For the pressure effect (H2b), we set  $M_{i,t} = TFP_{i,t}$ , where TFP is estimated using the Levinsohn–Petrin (LP) method. We expected  $\delta_1 < 0$  and  $\phi_1 < 0$ , suggesting that CPU reduces TFP and that lower TFP is associated with greater industrial intelligence transformation.

### 3.2.3. Moderation Models

To examine the moderating role of board-level risk governance, we estimated Equation (8):

$$II_{i,t} = \alpha + \gamma_1 CPU_{c,t-1} + \gamma_2 Board_{i,t} + \gamma_3 (CPU_{c,t} \times Board_{i,t}) + \theta' Controls_{i,c,t} + \mu_i + \lambda_t + \varepsilon_{i,c,t} \quad (8)$$

$Board_{i,t}$  alternatively captures board educational attainment (*Board\_Edu*), board innovation orientation (*Board\_Innov*), and the presence of a dedicated environmental committee or a risk committee (*Board\_EnvRiskComm*). The coefficient of interest is  $\gamma_3$ , which corresponds to H3a–H3c and is expected to be positive, indicating that stronger board-level risk governance amplifies the positive effect of CPU on industrial intelligence.

### 3.3. Data and Sample Selection

We constructed a panel of Chinese A-share listed firms from 2011 to 2024. Following standard practice, we excluded: (1) specially treated firms (ST, ST\*, or PT); (2) firms in the financial industry; (3) firms with missing data. Thereafter, we merged the industrial robot data with firm-year financial data and constructed our measure of corporate industrial intelligence based on industrial robot penetration. The annual financial data of Chinese listed firms were from the China Stock Market and Accounting Research Database (CSMAR). The industrial robot data used in this paper were obtained from the International Federation of Robotics (IFR). IFR conducts an annual survey of global robot manufacturers to form a “country–industry–year” level of world robot statistics based on first-hand data provided by robot manufacturers. IFR provides the most authoritative robot statistics available worldwide. Given that industrial robots are predominantly used in manufacturing, we focused on manufacturing firms and conducted the analysis using two-digit industry codes.

In the current research, the classification of China’s manufacturing industries aligned with the “GB/T4754-2011 Classification and Codes of National Economic Sectors”, adopting the two-digit coding system as per the 2011 standard. Furthermore, leveraging the correlation between the industry classification codes of China’s national economy and the “International Standard Industrial Classification of All Economic Activities (ISIC Revision 4)”, this paper matched the industrial employment statistics of China with the robot inventory data compiled by the IFR. On this basis, the data of China’s industrial robots and listed companies are connected. Finally, this yielded 24,962 firm-year observations for 1783 unique firms.

### 3.4. Descriptive Statistic

Table 1 reports the descriptive statistics for all variables. Table 2 presents the correlation matrix. The correlations suggest a positive association between climate policy uncertainty and corporate industrial intelligence. Appendix A.2 reports the variance inflation factor (VIF) values among the variables, with a mean VIF of 2.075, indicating a low overall level of multicollinearity.

**Table 1.** Descriptive statistics for variables.

| Variables           | Obs    | Mean   | Std. Dev. | Min   | Max    |
|---------------------|--------|--------|-----------|-------|--------|
| <i>II</i>           | 24,962 | 6.606  | 3.995     | 0.002 | 16     |
| <i>CPU</i>          | 24,962 | 0.270  | 0.066     | 0     | 1.322  |
| <i>LnR&amp;D</i>    | 24,962 | 17.703 | 1.489     | 0.815 | 24.630 |
| <i>RD_Intensity</i> | 24,962 | 0.017  | 0.030     | 0     | 0.312  |
| <i>TFP</i>          | 24,962 | 8.137  | 1.074     | 3.415 | 13.106 |
| <i>Board_Edu</i>    | 24,962 | 0.443  | 0.259     | 0     | 1      |
| <i>Board_STEM</i>   | 24,962 | 0.386  | 0.593     | 0     | 1      |

Table 1. Cont.

| Variables                | Obs    | Mean   | Std. Dev. | Min    | Max    |
|--------------------------|--------|--------|-----------|--------|--------|
| <i>Board_Innov</i>       | 24,962 | 0.407  | 0.337     | 0      | 1      |
| <i>Board_EnvRiskComm</i> | 24,962 | 0.218  | 0.413     | 0      | 1      |
| <i>Age</i>               | 24,962 | 1.810  | 0.976     | 1      | 3.497  |
| <i>Size</i>              | 24,962 | 21.790 | 1.358     | 10.842 | 29.949 |
| <i>Cash</i>              | 24,962 | 0.198  | 0.152     | 0.008  | 0.769  |
| <i>RoA</i>               | 24,962 | 0.0277 | 0.057     | −0.341 | 0.272  |
| <i>Lev</i>               | 24,962 | 0.418  | 0.213     | 0.044  | 0.903  |
| <i>RoE</i>               | 24,962 | 0.0421 | 0.165     | −1.037 | 0.469  |
| <i>Audit</i>             | 24,962 | 0.032  | 0.177     | 0      | 1      |
| <i>Top10</i>             | 24,962 | 0.592  | 0.154     | 0.013  | 1      |
| <i>Separation</i>        | 24,962 | 0.451  | 0.345     | 0      | 1      |
| <i>lngdp</i>             | 24,962 | 7.864  | 1.876     | 2.740  | 10.707 |

Table 2. Correlation matrix.

| Variables         | (1)        | (2)        | (3)        | (4)        | (5)      | (6)       | (7)        | (8)    | (9)       | (10)     | (11)       | (12)  |
|-------------------|------------|------------|------------|------------|----------|-----------|------------|--------|-----------|----------|------------|-------|
| <i>II</i>         | 1.000      |            |            |            |          |           |            |        |           |          |            |       |
| <i>CPU</i>        | 0.140 ***  | 1.000      |            |            |          |           |            |        |           |          |            |       |
| <i>Age</i>        | 0.014 ***  | 0.012 ***  | 1.000      |            |          |           |            |        |           |          |            |       |
| <i>Size</i>       | 0.055 ***  | 0.054 ***  | 0.377 ***  | 1.000      |          |           |            |        |           |          |            |       |
| <i>Cash</i>       | 0.002      | 0.009 **   | 0.007      | −0.004     | 1.000    |           |            |        |           |          |            |       |
| <i>RoA</i>        | −0.002     | −0.002     | 0.001      | −0.030 *** | 0.000    | 1.000     |            |        |           |          |            |       |
| <i>Lev</i>        | −0.012 **  | −0.004     | 0.024 ***  | −0.037 *** | −0.003   | 0.082 *** | 1.000      |        |           |          |            |       |
| <i>RoE</i>        | −0.002     | −0.002     | 0.001      | −0.030 *** | 0.000    | 0.918 *** | 0.083 ***  | 1.000  |           |          |            |       |
| <i>Audit</i>      | −0.007     | −0.005     | 0.037 ***  | 0.233 ***  | 0.000    | −0.001    | 0.000      | −0.001 | 1.000     |          |            |       |
| <i>Top10</i>      | −0.002     | 0.014 ***  | −0.404 *** | −0.027 *** | 0.010 ** | −0.002    | −0.022 *** | −0.002 | 0.072 *** | 1.000    |            |       |
| <i>Separation</i> | −0.018 *** | −0.009 **  | 0.083 ***  | 0.061 ***  | −0.005   | −0.003    | 0.008 *    | −0.003 | 0.065 *** | 0.081 ** | 1.000      |       |
| <i>lngdp</i>      | 0.009 *    | −0.091 *** | −0.047 *** | 0.027 ***  | 0.000    | −0.003    | −0.004     | −0.003 | 0.085 *** | 0.025 ** | −0.056 *** | 1.000 |

Notes: \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

## 4. Empirical Results

### 4.1. Baseline Regression Results

We estimated Equation (5) to examine the effect of CPU on corporate industrial intelligence, and Table 3 reports the baseline results. Column (1) presents the parsimonious specification with firm and year fixed effects, while Column (2) adds firm-level and city-level controls. Columns (3) and (4) replace year fixed effects with industry-by-year fixed effects to control for time-varying industry shocks, with Column (4) further including the full set of controls. As an additional comparison, Columns (5) and (6) used contemporaneous CPU instead of lagged CPU and followed the same parsimonious-to-full-control structure. Across all specifications, the coefficient on CPU was positive and statistically significant. When using lagged CPU, the estimated coefficients ranged from 1.098 to 1.155 and remained significant at the 1% level after adding controls and adopting more stringent fixed effects, supporting H1. The results using contemporaneous CPU were also positive and significant, indicating that the baseline finding is not driven by the lag structure.

Beyond statistical significance, the results in Table 3 also have economic and practical importance. Taking the full specification with firm and year fixed effects as an example, a 0.10-unit increase in climate policy uncertainty was associated with an increase of approximately 0.110 in corporate industrial intelligence. Based on the standard deviation of CPU reported in Table 1, a one-standard-deviation increase in CPU corresponded to an increase of about 0.073 in II, equivalent to approximately 1.8% of the standard deviation of the dependent variable. From a socio-technical systems perspective, this result suggests that climate policy uncertainty can act as an external institutional disturbance that promotes industrial intelligence transformation through technological system adjustment and organizational adaptation.

**Table 3.** Baseline regression results.

| Variables          | (1)<br><i>II</i>     | (2)<br><i>II</i>          | (3)<br><i>II</i>     | (4)<br><i>II</i>         | (5)<br><i>II</i>     | (6)<br><i>II</i>      |
|--------------------|----------------------|---------------------------|----------------------|--------------------------|----------------------|-----------------------|
| <i>L.CPU</i>       | 1.098 ***<br>(0.393) | 1.103 ***<br>(0.400)      | 1.141 ***<br>(0.388) | 1.155 ***<br>(0.395)     |                      |                       |
| <i>CPU</i>         |                      |                           |                      |                          | 1.122 ***<br>(0.397) | 1.107 ***<br>(0.397)  |
| <i>Age</i>         |                      | 0.0572 *<br>(0.0318)      |                      | 0.188 ***<br>(0.0360)    |                      | 1.169 ***<br>(0.0602) |
| <i>Size</i>        |                      | 0.235 ***<br>(0.0210)     |                      | 0.305 ***<br>(0.0244)    |                      | 0.447 ***<br>(0.0412) |
| <i>Cash</i>        |                      | 0.187<br>(0.201)          |                      | 0.175<br>(0.199)         |                      | 0.145<br>(0.200)      |
| <i>RoA</i>         |                      | 0.0629<br>(0.149)         |                      | 0.0520<br>(0.148)        |                      | 0.0721<br>(0.151)     |
| <i>Lev</i>         |                      | −0.0189<br>(0.0175)       |                      | −0.0128<br>(0.0177)      |                      | 0.0196<br>(0.0185)    |
| <i>RoE</i>         |                      | −0.0534<br>(0.135)        |                      | −0.0439<br>(0.134)       |                      | −0.0642<br>(0.136)    |
| <i>Audit</i>       |                      | −0.498 ***<br>(0.118)     |                      | −0.520 ***<br>(0.136)    |                      | −0.306<br>(0.222)     |
| <i>Top10</i>       |                      | −0.00155<br>(0.00181)     |                      | −0.00181<br>(0.00207)    |                      | 0.000673<br>(0.00314) |
| <i>Separation</i>  |                      | −0.00944 ***<br>(0.00321) |                      | −0.0117 ***<br>(0.00371) |                      | −0.00384<br>(0.00592) |
| <i>lngdp</i>       |                      | 0.0240<br>(0.0470)        |                      | 0.0171<br>(0.0468)       |                      | 0.0126<br>(0.0478)    |
| <i>Constant</i>    | 6.312 ***<br>(0.119) | 0.882<br>(0.643)          | 6.384 ***<br>(0.131) | −0.757<br>(0.689)        | 6.212 ***<br>(0.111) | −6.179 ***<br>(0.892) |
| Firm FE            | Yes                  | Yes                       | Yes                  | Yes                      | Yes                  | Yes                   |
| Year FE            | Yes                  | Yes                       | No                   | No                       | Yes                  | Yes                   |
| Industry × Year FE | No                   | No                        | Yes                  | Yes                      | No                   | No                    |
| Observations       | 24,962               | 24,962                    | 24,962               | 24,962                   | 23,179               | 23,179                |
| R-squared          | 0.008                | 0.015                     | 0.009                | 0.063                    | 0.004                | 0.051                 |
| F                  | 30.550               | 37.648                    | 18.806               | 25.604                   | 17.987               | 15.775                |

Notes: Robust standard errors clustered at the firm level are reported in parentheses. For the overall Wald tests of model significance, the corresponding *p*-values (Prob > F) were below 0.001 for all specifications. \* and \*\*\* denote significance at the 10% and 1% levels, respectively.

From a practical perspective, climate policy uncertainty does not necessarily inhibit firms' long-term investment and technological transformation. Instead, when firms expect future climate policies to become stricter, compliance costs to increase, and low-carbon transition requirements to intensify, they have stronger incentives to improve production efficiency, operational flexibility, and adaptability to external policy changes through industrial intelligence. Overall, the baseline regression results not only show that climate policy uncertainty significantly promotes corporate industrial intelligence in statistical terms, but also indicate that it may serve as an important external institutional signal that drives firms to adjust technological systems, reconfigure resources, and strengthen organizational adaptation in practice.

#### 4.2. Robustness Checks

##### 4.2.1. Alternative Measures and Sample Restrictions

To further assess robustness, we re-estimated Equation (5) using alternative measures and subsamples; Table 4 summarizes the results.

**Table 4.** Robustness checks: alternative measures, sample restrictions, and clustering.

| Variables          | (1)<br>Alternative<br>Dependent<br>Variable<br><i>II_2</i> | (2)<br>Alternative<br>Sample Time<br>Window<br><i>II</i> | (3)<br>Alternative<br>Regional<br>Scope<br><i>II</i> | (4)<br>Alternative<br>Sample<br>Selection<br><i>II</i> | (5)<br>Alternative<br>Industry<br><i>II</i> | (6)<br>Two-Way<br>Clustered<br><i>II</i> | (7)<br>Additional<br>Interaction<br>Fixed Effects<br><i>II</i> |
|--------------------|------------------------------------------------------------|----------------------------------------------------------|------------------------------------------------------|--------------------------------------------------------|---------------------------------------------|------------------------------------------|----------------------------------------------------------------|
| <i>L.CPU</i>       | 1.387 **<br>(0.612)                                        | 0.927 **<br>(0.414)                                      | 0.940 **<br>(0.454)                                  | 1.41 ***<br>(0.254)                                    | 1.392 **<br>(0.628)                         | 1.489 ***<br>(0.0599)                    | 1.170 ***<br>(0.0108)                                          |
| <i>Age</i>         | 0.216 ***<br>(0.0488)                                      | 1.176 ***<br>(0.0617)                                    | 0.0755<br>(0.0810)                                   | 0.0555 *<br>(0.0322)                                   | 0.167<br>(0.121)                            | 0.256 *<br>(0.134)                       | 0.195 ***<br>(0.0367)                                          |
| <i>Size</i>        | 0.283 ***<br>(0.0334)                                      | 0.446 ***<br>(0.0423)                                    | 0.0464<br>(0.0447)                                   | 0.238 ***<br>(0.0212)                                  | 0.0894<br>(0.0664)                          | 0.00424<br>(0.0521)                      | 0.312 ***<br>(0.0248)                                          |
| <i>Cash</i>        | −0.0479<br>(1.405)                                         | 0.133<br>(0.197)                                         | 0.0855<br>(0.198)                                    | 0.187<br>(0.201)                                       | 0.143<br>(0.204)                            | 0.0847<br>(0.198)                        | 0.174<br>(0.199)                                               |
| <i>RoA</i>         | 2.997<br>(2.264)                                           | −0.439<br>(0.467)                                        | 0.165<br>(0.149)                                     | 0.0650<br>(0.149)                                      | 0.170<br>(0.167)                            | 0.164<br>(0.149)                         | 0.0534<br>(0.148)                                              |
| <i>Lev</i>         | −0.0812 *<br>(0.0436)                                      | 0.0140<br>(0.0197)                                       | 0.0120<br>(0.0184)                                   | −0.0179<br>(0.0175)                                    | 0.0232<br>(0.0251)                          | 0.0105<br>(0.0184)                       | −0.0114<br>(0.0177)                                            |
| <i>RoE</i>         | −3.149<br>(2.241)                                          | 0.393<br>(0.418)                                         | −0.147<br>(0.135)                                    | −0.0554<br>(0.135)                                     | −0.154<br>(0.151)                           | −0.146<br>(0.135)                        | −0.0453<br>(0.134)                                             |
| <i>Audit</i>       | −0.422 **<br>(0.196)                                       | −0.347<br>(0.230)                                        | −0.420 *<br>(0.220)                                  | −0.483 ***<br>(0.119)                                  | −0.390<br>(0.290)                           | −0.423 *<br>(0.220)                      | −0.504 ***<br>(0.138)                                          |
| <i>Top10</i>       | −0.000393<br>(0.00281)                                     | 0.000615<br>(0.00321)                                    | −0.00847 ***<br>(0.00318)                            | −0.00147<br>(0.00184)                                  | −0.0127 ***<br>(0.00464)                    | −0.00682 **<br>(0.00319)                 | −0.00178<br>(0.00211)                                          |
| <i>Separation</i>  | −0.0106 **<br>(0.00499)                                    | −0.00303<br>(0.00609)                                    | −0.00522<br>(0.00593)                                | −0.00975 ***<br>(0.00325)                              | −0.000476<br>(0.00878)                      | −0.00310<br>(0.00586)                    | −0.0124 ***<br>(0.00378)                                       |
| <i>lngdp</i>       | 0.0765<br>(0.0637)                                         | −0.0290<br>(0.0493)                                      | 0.00432<br>(0.0478)                                  | 0.0326<br>(0.0472)                                     | −0.0266<br>(0.0757)                         | 0.0104<br>(0.0473)                       | 0.0238<br>(0.0469)                                             |
| <i>Constant</i>    | 1.387 **<br>(0.612)                                        | 0.927 **<br>(0.414)                                      | 0.940 **<br>(0.454)                                  | 0.777<br>(0.632)                                       | 1.392 **<br>(0.628)                         | 1.489 ***<br>(0.0599)                    | −0.951<br>(0.683)                                              |
| Firm FE            | Yes                                                        | Yes                                                      | Yes                                                  | Yes                                                    | Yes                                         | Yes                                      | No                                                             |
| Year FE            | Yes                                                        | Yes                                                      | Yes                                                  | Yes                                                    | Yes                                         | Yes                                      | Yes                                                            |
| Province × Year FE | No                                                         | No                                                       | No                                                   | No                                                     | No                                          | No                                       | Yes                                                            |
| Observations       | 24,962                                                     | 23,179                                                   | 24,318                                               | 24,024                                                 | 17,304                                      | 24,962                                   | 24,962                                                         |
| R-squared          | 0.061                                                      | 0.054                                                    | 0.071                                                | 0.129                                                  | 0.065                                       | 0.085                                    | 0.098                                                          |
| F                  | 20.997                                                     | 23.152                                                   | 17.290                                               | 19.998                                                 | 14.535                                      | 28.694                                   | 15.116                                                         |

Notes: Standard errors are clustered at the firm level unless otherwise stated; column (6) reports two-way clustered standard errors (firm × city). For the overall Wald tests of model significance, the corresponding *p*-values (Prob > F) were below 0.001 for all specifications. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

First, to mitigate concerns regarding the Bartik-style robot-based proxy, we further used annual-report disclosures to capture firms' digital and intelligent transformation activities, following prior keyword-based studies [67,68]. Column (1) replaced the dependent variable with a text-based measure (*II\_2*) constructed from industrial-intelligence-related keywords in firms' annual reports. The coefficient on CPU remained positive and significant, suggesting that our findings are not driven by a specific measurement of industrial intelligence. Second, column (2) excluded the year 2020 to rule out potential confounding effects of the COVID-19 shock. The estimated CPU effect remained significantly positive. Third, column (3) dropped firms in Hainan Province, where CPU variation was comparatively limited, and the results were unchanged. Fourth, Column (4) excluded observations with negative ROE to reduce the potential influence of abnormal profitability conditions, and the coefficient on CPU was still positive and significant. Fifth, Column (5) restricted the sample to manufacturing firms, the sector most closely related to industrial robot adoption, and again yielded a positive and significant CPU coefficient. Sixth, Column (6) reported results based on two-way clustered standard errors at the firm and city levels, and the main conclusion remained robust. Finally, Column (7) further included province-by-year fixed effects to control for time-varying regional factors, such as regional economic development, industrial policy, environmental regulation, and technological conditions. The coefficient on CPU remained positive and statistically significant, suggesting that the baseline result is not driven by unobserved province-year factors.

Overall, across alternative dependent-variable definitions, multiple sample restrictions, and a more conservative clustering scheme, the estimated effect of CPU on corporate industrial intelligence was consistently positive and statistically significant.

#### 4.2.2. Propensity Score Matching (PSM)

We acknowledge that our baseline estimates may be subject to endogeneity concerns, particularly stemming from firms' self-selection. To address this concern, we employed propensity score matching (PSM) by partitioning firms into two groups based on CPU: a high-CPU group (treatment) and a low-CPU group (control), using the annual median of CPU as the cutoff. We defined *CPU\_dummy* as an indicator variable that equals 1 for firms with CPU above the annual median and 0 for firms with CPU below the annual median. Following Wellman (2017) [69], we estimated a probit model in the first stage using the same set of covariates as in the baseline specification and included industry fixed effects. For the matching procedure, we implemented one-to-one nearest-neighbor matching without replacement so that each treated firm was matched to a unique control firm. In addition, we imposed a caliper of 0.01 to ensure close matches and enhance comparability between the treatment and control groups, thereby mitigating potential selection bias.

Table 5 reports the regression results before and after matching. Column (1) presents the estimate using *CPU\_dummy* in the pre-match sample, and Column (2) reports the corresponding result in the post-match sample. The results indicate that the matching procedure is effective. Specifically, the coefficient on *CPU\_dummy* remained positive and statistically significant after matching, and its significance strengthened from the 10% level to the 5% level, suggesting that our main finding is not driven by observable differences between high- and low-CPU firms. Consistent with Table 5, Figure 2 further shows improved covariate balance after matching, as the standardized mean differences were markedly reduced in the matched sample.

**Table 5.** Robust check: propensity score matching.

| Variables         | (1)<br>Pre-Match<br>II | (2)<br>Post-Match<br>II |
|-------------------|------------------------|-------------------------|
| <i>CPU_dummy</i>  | 1.680 *<br>(0.842)     | 1.750 **<br>(0.837)     |
| <i>Age</i>        | 3.254 *<br>(1.848)     | 3.549 *<br>(1.814)      |
| <i>Size</i>       | 1.056<br>(1.340)       | 0.917<br>(1.344)        |
| <i>Cash</i>       | 0.998<br>(7.683)       | 1.468<br>(7.752)        |
| <i>RoA</i>        | 7.143<br>(99.19)       | 13.53<br>(97.69)        |
| <i>Lev</i>        | −3.944<br>(4.551)      | −3.570<br>(4.619)       |
| <i>RoE</i>        | −5.405<br>(95.16)      | −10.67<br>(93.62)       |
| <i>Audit</i>      | 7.547<br>(4.990)       | 7.419<br>(5.126)        |
| <i>Top10</i>      | −0.111<br>(0.113)      | −0.0973<br>(0.114)      |
| <i>Separation</i> | −0.193<br>(0.167)      | −0.182<br>(0.168)       |

Table 5. Cont.

| Variables       | (1)<br>Pre-Match<br>II | (2)<br>Post-Match<br>II |
|-----------------|------------------------|-------------------------|
| <i>lngdp</i>    | −0.937<br>(1.243)      | −0.909<br>(1.277)       |
| <i>Constant</i> | −7.761<br>(26.56)      | −6.597<br>(26.78)       |
| Firm FE         | Yes                    | Yes                     |
| Year FE         | Yes                    | Yes                     |
| Observations    | 24,962                 | 21,196                  |
| R-squared       | 0.332                  | 0.490                   |
| F               | 10.639                 | 22.125                  |

Notes: Robust standard errors clustered at the firm level are reported in parentheses. For the overall Wald tests of model significance, the corresponding *p*-values (Prob > F) were below 0.001 for all specifications. \* and \*\* denote significance at the 10% and 5% levels, respectively.

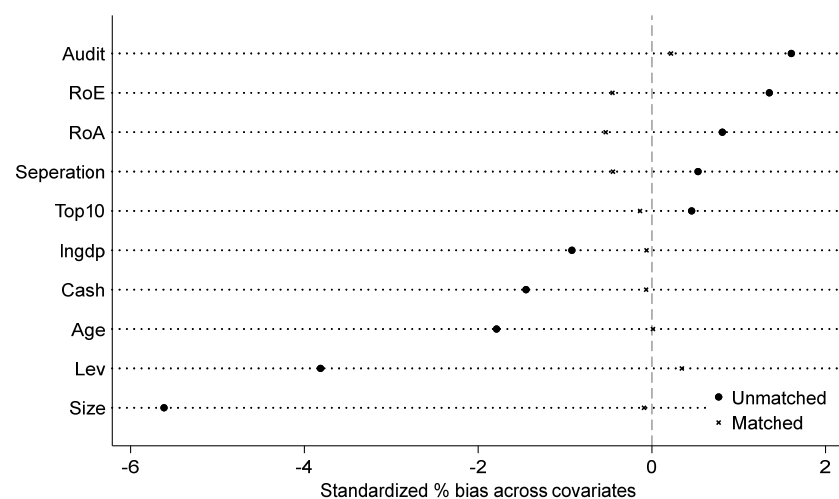


Figure 2. Standardized mean differences of covariates: pre-match vs. post-match.

#### 4.2.3. Instrumental Variable Regression

To further alleviate potential endogeneity concerns, we employed a two-stage least squares (TSLS) instrumental variable approach. Although a broad set of firm-level controls was included, omitted or unobserved factors may still bias the estimated effect of climate policy uncertainty on industrial intelligence.

Following Zheng et al. (2025) [70], we first used the U.S. climate policy uncertainty index (*IV1\_CPU*), developed by Gavrilidis (2021) [71], as an instrumental variable for Chinese CPU to mitigate potential endogeneity concerns. This instrument is appropriate because, as one of the world's most influential economies, changes in U.S. climate governance and policy agendas may affect China's climate policy environment through international policy transmission, expectation formation, and external institutional pressure, thereby ensuring instrument relevance. At the same time, given China's capital controls and the relative segmentation of its capital market, U.S. climate policy uncertainty is unlikely to directly affect board-level risk governance or corporate industrial intelligence among Chinese firms. Instead, its effect is more likely to operate indirectly through China's own climate policy uncertainty, which supports the exogeneity condition for a valid instrumental variable.

In addition, following the literature that uses temperature fluctuations as exogenous climatic shocks [72,73], we used abnormal temperature (*IV2\_CPU*) as an additional instrumental variable. Abnormal temperature reflects exogenous climate-related shocks that

may increase public concern, regulatory attention, and climate-policy responses, thereby affecting climate policy uncertainty [74]. At the same time, abnormal temperature is largely driven by natural climatic fluctuations and is unlikely to be directly determined by firms' industrial intelligence decisions. Therefore, *IV2\_CPU* provides a supplementary instrument to test the robustness of the IV results.

The results are reported in Table 6. Columns (1) and (2) present the TSLS results based on *IV1\_CPU*, while Columns (3) and (4) report the results based on *IV2\_CPU*. In Column (1), the coefficient on *IV1\_CPU* was positive and statistically significant at the 1% level, indicating strong instrument relevance; the corresponding first-stage F-statistic was 41.840, suggesting that weak-instrument concerns are unlikely. In Column (3), the coefficient on *IV2\_CPU* was also positive and statistically significant at the 1% level, with a first-stage F-statistic of 138.071, further supporting instrument relevance. In Columns (2) and (4), the fitted value of *L\_CPU* was positively and significantly associated with *II*, which is consistent with our baseline findings. Overall, the IV results based on two alternative instruments support the conclusion that climate policy uncertainty promotes corporate industrial intelligence.

**Table 6.** Robust check: instrumental variables regression.

| Variables         | (1)<br>First Stage<br><i>L_CPU</i>                  | (2)<br>Second Stage<br><i>II</i> | (3)<br>First Stage<br><i>L_CPU</i> | (4)<br>Second Stage<br><i>II</i> |
|-------------------|-----------------------------------------------------|----------------------------------|------------------------------------|----------------------------------|
| <i>IV1_CPU</i>    | 0.0112 ***<br>(0.00198)                             |                                  |                                    |                                  |
| <i>IV2_CPU</i>    |                                                     |                                  | 0.135 ***<br>(0.0236)              |                                  |
| <i>L_CPU</i>      |                                                     | 20.75 **<br>(9.763)              |                                    | 3.711 ***<br>(0.279)             |
| <i>Age</i>        | 0.00445 ***<br>(0.00134)                            | 0.0244<br>(0.0444)               | 0.0223 ***<br>(0.00133)            | 0.870 ***<br>(0.0801)            |
| <i>Size</i>       | 0.00114 *<br>(0.000685)                             | 0.0282<br>(0.0292)               | 0.918 ***<br>(0.0110)              | 0.333 ***<br>(0.0771)            |
| <i>Cash</i>       | 0.0633 ***<br>(0.0131)                              | −0.612<br>(1.156)                | 0.0156<br>(0.0360)                 | 0.152<br>(0.215)                 |
| <i>RoA</i>        | −0.00243 *<br>(0.00140)                             | 0.202<br>(0.152)                 | −0.817 **<br>(0.352)               | 0.193<br>(2.101)                 |
| <i>Lev</i>        | −0.000400 *<br>(0.000225)                           | 0.0135<br>(0.0184)               | −0.128 ***<br>(0.0258)             | −0.0750<br>(0.155)               |
| <i>RoE</i>        | 0.00223 *<br>(0.00130)                              | −0.180<br>(0.138)                | 0.668 *<br>(0.348)                 | −0.313<br>(2.082)                |
| <i>Audit</i>      | 0.00263<br>(0.00316)                                | −0.290 *<br>(0.154)              | 0.0403<br>(0.0520)                 | −0.365<br>(0.311)                |
| <i>Top10</i>      | $-5.36 \times 10^{-5}$<br>( $5.06 \times 10^{-5}$ ) | −0.00290<br>(0.00257)            | 0.00342 ***<br>(0.000726)          | −0.00376<br>(0.00434)            |
| <i>Separation</i> | 0.000237 ***<br>( $9.05 \times 10^{-5}$ )           | 0.00176<br>(0.00501)             | 0.00235 *<br>(0.00139)             | −0.00241<br>(0.00833)            |
| <i>lngdp</i>      | 0.00185<br>(0.00116)                                | 0.124 *<br>(0.0659)              | −0.00473<br>(0.00978)              | 0.00823<br>(0.0585)              |
| <i>Constant</i>   | 0.169 ***<br>(0.0169)                               | −2.093<br>(2.915)                | −3.040 ***<br>(0.237)              | −6.132 ***<br>(1.425)            |
| Firm FE           | Yes                                                 | Yes                              | Yes                                | Yes                              |
| Year FE           | Yes                                                 | Yes                              | Yes                                | Yes                              |
| Observations      | 24,962                                              | 24,962                           | 24,962                             | 24,962                           |

Table 6. Cont.

| Variables | (1)<br>First Stage<br><i>L.CPU</i> | (2)<br>Second Stage<br><i>II</i> | (3)<br>First Stage<br><i>L.CPU</i> | (4)<br>Second Stage<br><i>II</i> |
|-----------|------------------------------------|----------------------------------|------------------------------------|----------------------------------|
| R-squared | 0.244                              | 0.096                            | 0.571                              | 0.269                            |
| F         | 41.840                             |                                  | 138.071                            |                                  |

Notes: Robust standard errors clustered at the firm level are reported in parentheses. For the overall Wald tests of model significance, the corresponding  $p$ -values (Prob > F) were below 0.001 for all specifications. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

#### 4.3. Mechanism Analysis

Having established that CPU is positively associated with corporate industrial intelligence, we further examined the underlying mechanisms through which CPU affects firms' transformation. Drawing on our hypotheses, we considered two mediating channels: R&D investment (opportunity channel) and total factor productivity (pressure channel). We estimated standard mediation models, and Table 7 reports the results.

Table 7 Column (1) shows that CPU significantly increased firms' R&D investment ( $\delta_1 = 0.339, p < 0.01$ ). Column (2) further indicates that R&D was positively and significantly related to industrial intelligence ( $\phi_1 = 0.229, p < 0.01$ ), while the coefficient on CPU remained positive. These results are consistent with H2a, suggesting that CPU promotes industrial intelligence partly by stimulating R&D investment. Columns (3) and (4) further used R&D intensity as an alternative measure of innovation input. Column (3) shows that CPU significantly increased the R&D intensity ( $\delta_1 = 0.0931, p < 0.01$ ), and Column (4) shows that R&D intensity was positively and significantly associated with industrial intelligence ( $\phi_1 = 0.152, p < 0.01$ ). This provides additional evidence that climate policy uncertainty encourages firms to increase innovation input and thereby promotes industrial intelligence transformation.

Columns (5) and (6) report the productivity-based mechanism. In column (5), CPU significantly reduced firms' TFP ( $\delta_1 = -0.127, p < 0.10$ ), implying that heightened policy uncertainty weakens productivity under the conventional production mode. In column (6), TFP was negatively and significantly associated with industrial intelligence ( $\phi_1 = -0.0508, p < 0.01$ ), indicating that firms experiencing lower productivity are more likely to accelerate industrial intelligence transformation. Taken together, the evidence supports H2b and points to a pressure channel operating through productivity deterioration. This result should be interpreted as evidence that climate-policy-induced productivity pressure may stimulate efficiency-seeking technological adjustment, rather than as evidence that lower productivity always facilitates intelligent transformation.

Table 7 further indicates that the mediating mechanisms are economically meaningful. Regarding the opportunity effect, when CPU increased by 0.10, firms' R&D investment increased by approximately 3.4%, while R&D intensity increased by approximately 0.0093. These results suggest that climate policy uncertainty encourages firms to strengthen technological capabilities through greater innovation input. Regarding the pressure effect, when CPU increased by 0.10, firms' TFP decreased by approximately 0.0127, indicating that climate policy uncertainty may impose production-efficiency pressure and induce technological system adjustment. A comparison of the indirect effects showed that the indirect effect through R&D investment was approximately 0.078; that through R&D intensity, it was approximately 0.014; and that through TFP, it was approximately 0.006. Overall, CPU promotes corporate industrial intelligence mainly through proactive capability building, while productivity pressure serves as a smaller but meaningful complementary channel.

Table 7. Mechanism analysis results.

| Variables           | (1)<br><i>R&amp;D</i>     | (2)<br><i>II</i>      | (3)<br><i>RD_Intensity</i> | (4)<br><i>II</i>        | (5)<br><i>TFP</i>         | (6)<br><i>II</i>         |
|---------------------|---------------------------|-----------------------|----------------------------|-------------------------|---------------------------|--------------------------|
| <i>L.CPU</i>        | 0.339 ***<br>(0.101)      | 1.320 ***<br>(0.494)  | 0.0931 ***<br>(0.00227)    | 0.571 ***<br>(0.186)    | −0.127 *<br>(0.0665)      | 0.963 **<br>(0.458)      |
| <i>R&amp;D</i>      |                           | 0.229 ***<br>(0.0436) |                            |                         |                           |                          |
| <i>RD_Intensity</i> |                           |                       |                            | 0.152 ***<br>(0.000575) |                           |                          |
| <i>TFP</i>          |                           |                       |                            |                         |                           | −0.0508 ***<br>(0.00738) |
| <i>Age</i>          | 0.225 ***<br>(0.0131)     | 0.880 ***<br>(0.0792) | 4.875 ***<br>(0.0197)      | 1.163 ***<br>(0.0610)   | 0.0566<br>(0.0638)        | −0.0934<br>(0.0826)      |
| <i>Size</i>         | 0.918 ***<br>(0.0109)     | 0.303 ***<br>(0.0764) | 1.175 ***<br>(0.0107)      | 0.452 ***<br>(0.0415)   | 0.816 ***<br>(0.00422)    | −0.00953<br>(0.0710)     |
| <i>Cash</i>         | 0.0156<br>(0.0359)        | 0.152<br>(0.215)      | 0.0176<br>(0.0560)         | 0.145<br>(0.200)        | 0.0131<br>(0.0212)        | 0.0673<br>(0.205)        |
| <i>RoA</i>          | −0.905 ***<br>(0.350)     | 0.158<br>(2.098)      | 0.157 ***<br>(0.0273)      | 0.0728<br>(0.151)       | −0.0775 ***<br>(0.0164)   | 0.121<br>(0.883)         |
| <i>Lev</i>          | −0.139 ***<br>(0.0257)    | −0.0596<br>(0.154)    | 0.0368 ***<br>(0.00430)    | 0.0202<br>(0.0185)      | −0.00512 *<br>(0.00275)   | 0.00406<br>(0.0362)      |
| <i>RoE</i>          | 0.749 **<br>(0.347)       | −0.261<br>(2.079)     | −0.143 ***<br>(0.0254)     | −0.0649<br>(0.136)      | 0.0725 ***<br>(0.0151)    | −0.107<br>(0.789)        |
| <i>Audit</i>        | 0.0376<br>(0.0515)        | −0.349<br>(0.309)     | 0.122 **<br>(0.0498)       | −0.288<br>(0.225)       | 0.0307<br>(0.0190)        | −0.386 *<br>(0.231)      |
| <i>Top10</i>        | 0.00314 ***<br>(0.000716) | −0.00354<br>(0.00429) | −0.0231 ***<br>(0.000771)  | 0.000631<br>(0.00317)   | 0.00124 ***<br>(0.000293) | −0.00675 **<br>(0.00326) |
| <i>Separation</i>   | 0.00418 ***<br>(0.00137)  | −0.00233<br>(0.00821) | 0.00344 **<br>(0.00137)    | −0.00528<br>(0.00601)   | 0.00178 ***<br>(0.000517) | −0.00247<br>(0.00604)    |
| <i>lngdp</i>        | 0.00347<br>(0.00989)      | 0.00114<br>(0.0592)   | −0.0181<br>(0.0122)        | 0.0229<br>(0.0479)      | −0.000710<br>(0.00450)    | 0.00377<br>(0.0481)      |
| <i>Constant</i>     | −3.088 ***<br>(0.236)     | −5.788 ***<br>(1.420) | −16.51 ***<br>(0.240)      | −6.326 ***<br>(0.896)   | −7.199 ***<br>(0.0939)    | 4.074 ***<br>(1.150)     |
| Firm FE             | Yes                       | Yes                   | Yes                        | Yes                     | Yes                       | Yes                      |
| Year FE             | Yes                       | Yes                   | Yes                        | Yes                     | Yes                       | Yes                      |
| Observations        | 24,962                    | 24,962                | 24,962                     | 24,962                  | 24,962                    | 24,962                   |
| R-squared           | 0.470                     | 0.038                 | 0.589                      | 0.067                   | 0.736                     | 0.071                    |
| F                   | 50.718                    | 70.992                | 46.858                     | 67.480                  | 25.841                    | 34.749                   |

Notes: Robust standard errors clustered at the firm level are reported in parentheses. For the overall Wald tests of model significance, the corresponding *p*-values (Prob > F) were below 0.001 for all specifications. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

#### 4.4. Board-Level Moderating Effects

Table 8 reports the moderating role of board-level risk governance in the relationship between climate policy uncertainty and corporate industrial intelligence. Consistent with H3, the interaction terms between CPU and board characteristics were positive and statistically significant across specifications, indicating that stronger board governance amplifies the positive effect of CPU on corporate industrial intelligence.

Column (1) examines board educational attainment. The coefficient on  $CPU \times Board\_Edu$  was positive and significant ( $\gamma_3 = 1.834, p < 0.01$ ), suggesting that firms with more highly educated boards exhibit a stronger positive response of II to CPU. Column (2) further examines whether board members have STEM educational backgrounds. The interaction term  $CPU \times Board\_STEM$  was positive and significant ( $\gamma_3 = 1.022, p < 0.01$ ), indicating that technically relevant board human capital strengthens firms' ability to translate climate policy uncertainty into industrial intelligence transformation. Column (3)

focuses on board innovation orientation. The interaction term  $CPU \times Board\_Innov$  was also positive and significant ( $\gamma_3 = 0.830, p < 0.01$ ), implying that innovation-oriented boards reinforce firms' tendency to pursue industrial intelligence transformation under heightened CPU. Column (4) tests whether firms have established an environmental committee or a risk committee. The coefficient on  $CPU \times Board\_EnvRiskComm$  remained positive and significant ( $\gamma_3 = 1.224, p < 0.10$ ), indicating that the presence of such committees strengthens the CPU–II linkage, although the effect is relatively weaker in statistical precision.

**Table 8.** The moderating role of board characteristics.

| Variables                        | (1)<br>II               | (2)<br>II                | (3)<br>II                | (4)<br>II                |
|----------------------------------|-------------------------|--------------------------|--------------------------|--------------------------|
| <i>L.CPU</i>                     | 0.978 *<br>(0.507)      | 0.946 **<br>(0.397)      | 1.021 ***<br>(0.377)     | 1.130 ***<br>(0.400)     |
| <i>Board_Edu</i>                 | 0.489 ***<br>(0.158)    |                          |                          |                          |
| <i>L.CPU × Board_Edu</i>         | 1.834 ***<br>(0.150)    |                          |                          |                          |
| <i>Board_STEM</i>                |                         | 0.373 ***<br>(0.018)     |                          |                          |
| <i>L.CPU × Board_STEM</i>        |                         | 1.022 ***<br>(0.151)     |                          |                          |
| <i>Board_Innov</i>               |                         |                          | 0.525 ***<br>(0.187)     |                          |
| <i>L.CPU × Board_Innov</i>       |                         |                          | 0.830 ***<br>(0.155)     |                          |
| <i>Board_EnvRiskComm</i>         |                         |                          |                          | 0.337 *<br>(0.204)       |
| <i>L.CPU × Board_EnvRiskComm</i> |                         |                          |                          | 1.224 *<br>(0.715)       |
| <i>Age</i>                       | −0.00970<br>(0.0588)    | −0.0169<br>(0.0644)      | 0.00256<br>(0.0344)      | 0.0201<br>(0.0413)       |
| <i>Size</i>                      | 0.295 ***<br>(0.0403)   | 0.0289<br>(0.0393)       | 0.230 ***<br>(0.0230)    | 0.209 ***<br>(0.0278)    |
| <i>Cash</i>                      | 1.983<br>(1.477)        | 0.0714<br>(0.189)        | 0.186<br>(1.315)         | −0.235<br>(1.400)        |
| <i>RoA</i>                       | 1.176<br>(2.230)        | 0.155<br>(0.145)         | 3.982 **<br>(1.745)      | 3.608<br>(2.216)         |
| <i>Lev</i>                       | −0.0172<br>(0.0469)     | 0.00973<br>(0.0178)      | −0.0589 **<br>(0.0263)   | −0.0968 **<br>(0.0427)   |
| <i>RoE</i>                       | −1.176<br>(2.220)       | −0.138<br>(0.131)        | −4.151 **<br>(1.737)     | −3.756 *<br>(2.192)      |
| <i>Audit</i>                     | −0.569 **<br>(0.243)    | −0.524 ***<br>(0.187)    | −0.403 ***<br>(0.135)    | −0.368 **<br>(0.168)     |
| <i>Top10</i>                     | 0.00158<br>(0.00339)    | −0.00646 **<br>(0.00268) | −0.00201<br>(0.00199)    | −0.000177<br>(0.00240)   |
| <i>Separation</i>                | −0.00987 *<br>(0.00582) | −0.00253<br>(0.00503)    | −0.0107 ***<br>(0.00348) | −0.00852 **<br>(0.00413) |
| <i>Ingdp</i>                     | −0.0614<br>(0.0776)     | 0.00788<br>(0.0423)      | 0.00774<br>(0.0145)      | −0.00395<br>(0.0178)     |
| <i>Constant</i>                  | 0.875<br>(1.137)        | 3.655 ***<br>(0.873)     | 1.340 ***<br>(0.493)     | 2.269 ***<br>(0.596)     |
| Firm FE                          | Yes                     | Yes                      | Yes                      | Yes                      |
| Year FE                          | Yes                     | Yes                      | Yes                      | Yes                      |
| Observations                     | 24,962                  | 24,962                   | 24,962                   | 24,962                   |

Table 8. *Cont.*

| Variables | (1)<br><i>II</i> | (2)<br><i>II</i> | (3)<br><i>II</i> | (4)<br><i>II</i> |
|-----------|------------------|------------------|------------------|------------------|
| R-squared | 0.074            | 0.063            | 0.069            | 0.043            |
| F         | 43.204           | 50.064           | 67.821           | 37.642           |

Notes: Robust standard errors clustered at the firm level are reported in parentheses. For the overall Wald tests of model significance, the corresponding *p*-values (Prob > F) were below 0.001 for all specifications. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

From an economic perspective, the results indicate that board governance is a key internal factor that amplifies the positive effect of climate policy uncertainty on industrial intelligence. Highly educated boards, boards with STEM backgrounds, innovation-oriented boards, and dedicated environmental or risk committees, can reduce information barriers and decision-making costs when firms respond to policy changes. This suggests that sound corporate governance helps firms transform external policy uncertainty into opportunities for technological upgrading, while differences in governance capacity partly explain heterogeneous responses in intelligent transformation across firms.

Overall, these results support H3a–H3c and further show that the technical relevance of board human capital also enhances firms' capability to translate climate policy uncertainty into proactive industrial intelligence transformation.

#### 4.5. Heterogeneity Analysis

Building on the benchmark results, we further explored whether the effect of CPU on corporate industrial intelligence differed across firms. We conducted subsample regressions along three dimensions: pollution intensity, firm size, and firm age. The results are reported in Table 9.

Following Wang et al., (2022) [75], we proxied pollution intensity using carbon emissions intensity, defined as the ratio of a firm's carbon emissions to its operating revenue. Then, we divided the firms into two groups with high-pollution industries and low-pollution industries. The results are presented in columns (1) and (2) of Table 9. It can be found that the industrial intelligence of firms with low-pollution industries was not significantly affected by CPU, while the industrial intelligence of firms with high-pollution industries increased significantly with the increase in CPU. We split the sample into large and small firms using the median of firm size. Columns (3) and (4) indicate that CPU had a significantly positive effect on industrial intelligence for large firms, but the coefficient was insignificant for small firms. Given the relatively short history of China's capital market, listed firms differ substantially in organizational maturity. We therefore divided firms into long-established and newly established groups based on the median firm age. Columns (5) and (6) show that the CPU coefficient was significantly positive for long-established firms, while it was insignificant for newly established firms.

Overall, the heterogeneity results suggest that the positive CPU–industrial intelligence relationship is concentrated among firms with higher pollution exposure, larger scale, and greater organizational maturity. From a socio-technical systems perspective, these findings indicate that firms' responses to climate policy uncertainty depend on the alignment among external institutional pressure, internal resource endowments, and organizational adaptive capacity. High-pollution firms face stronger regulatory pressure, large firms possess greater resources for technological transformation, and long-established firms have more mature organizational routines for coordinating system-level change. Therefore, climate policy uncertainty is more likely to be transformed into industrial intelligence upgrading when firms have both stronger external incentives and stronger internal capacity for socio-technical adaptation.

Table 9. Heterogeneity analysis results.

| Variables         | (1)                                    | (2)                                   | (3)                            | (4)                            | (5)                                 | (6)                                  |
|-------------------|----------------------------------------|---------------------------------------|--------------------------------|--------------------------------|-------------------------------------|--------------------------------------|
|                   | High-Pollution Industries<br><i>II</i> | Low-Pollution Industries<br><i>II</i> | Large-Scale Firms<br><i>II</i> | Small-Scale Firms<br><i>II</i> | Long-Established Firms<br><i>II</i> | Newly Established Firms<br><i>II</i> |
| <i>L.CPU</i>      | 1.114 **<br>(0.515)                    | 0.920<br>(1.018)                      | 0.855 *<br>(0.442)             | 4.351<br>(5.075)               | 3.562 ***<br>(1.077)                | 0.221<br>(0.478)                     |
| <i>Age</i>        | −0.0408<br>(0.0985)                    | −0.128<br>(0.189)                     | −0.0468<br>(0.0816)            | 1.412<br>(2.452)               | −0.143<br>(0.228)                   | −0.154<br>(0.107)                    |
| <i>Size</i>       | 0.0793<br>(0.0528)                     | −0.0931<br>(0.118)                    | 0.0519<br>(0.0443)             | −0.915<br>(1.446)              | −0.152<br>(0.155)                   | 0.0763 *<br>(0.0456)                 |
| <i>Cash</i>       | 0.0808<br>(0.205)                      | 0.000995<br>(4.848)                   | 0.0861<br>(0.197)              | 23.69<br>(102.4)               | 14.71<br>(10.67)                    | 0.0705<br>(0.192)                    |
| <i>RoA</i>        | 0.340<br>(1.700)                       | −3.179<br>(2.261)                     | 0.165<br>(0.149)               | 5.008<br>(54.13)               | 6.365<br>(6.801)                    | 0.164<br>(0.145)                     |
| <i>Lev</i>        | 0.0104<br>(0.0281)                     | −0.0985<br>(0.0930)                   | 0.0124<br>(0.0183)             | −0.646<br>(3.498)              | 0.161<br>(0.444)                    | 0.0134<br>(0.0179)                   |
| <i>RoE</i>        | −0.320<br>(1.699)                      | 2.850<br>(2.027)                      | −0.147<br>(0.135)              | 1.415<br>(48.19)               | −7.838<br>(6.565)                   | −0.146<br>(0.131)                    |
| <i>Audit</i>      | −0.619 **<br>(0.268)                   | 0.0240<br>(0.465)                     | −0.430 *<br>(0.221)            | −0.839<br>(2.211)              | 0.537<br>(0.638)                    | −0.568 **<br>(0.230)                 |
| <i>Top10</i>      | −0.00702 *<br>(0.00388)                | −0.00784<br>(0.00671)                 | −0.00755 **<br>(0.00314)       | 0.0871<br>(0.0723)             | 0.000735<br>(0.00918)               | −0.00865 ***<br>(0.00334)            |
| <i>Separation</i> | 0.000733<br>(0.00712)                  | −0.0133<br>(0.0127)                   | −0.00285<br>(0.00583)          | −0.251<br>(0.211)              | −0.00314<br>(0.0175)                | −0.00265<br>(0.00610)                |
| <i>lngdp</i>      | −0.000313<br>(0.0554)                  | 0.0808<br>(0.1000)                    | −0.00536<br>(0.0478)           | 0.536<br>(0.334)               | −0.00298<br>(0.120)                 | 0.0165<br>(0.0507)                   |
| <i>Constant</i>   | 2.801 **<br>(1.161)                    | 6.132 **<br>(2.566)                   | 3.446 ***<br>(0.982)           | 17.15<br>(32.21)               | 7.721 **<br>(3.466)                 | 3.147 ***<br>(1.026)                 |
| Firm FE           | Yes                                    | Yes                                   | Yes                            | Yes                            | Yes                                 | Yes                                  |
| Year FE           | Yes                                    | Yes                                   | Yes                            | Yes                            | Yes                                 | Yes                                  |
| Observations      | 12,222                                 | 12,740                                | 12,614                         | 12,348                         | 12,404                              | 12,558                               |
| R-squared         | 0.069                                  | 0.054                                 | 0.073                          | 0.016                          | 0.037                               | 0.087                                |
| F                 | 38.709                                 | 16.746                                | 30.968                         | 15.237                         | 43.220                              | 12.973                               |

Notes: Robust standard errors clustered at the firm level are reported in parentheses. For the overall Wald tests of model significance, the corresponding *p*-values (Prob > F) were below 0.001 for all specifications. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

## 5. Discussion and Limitations

### 5.1. Discussion

First, this study shows that climate policy uncertainty significantly promotes corporate industrial intelligence. This finding suggests that climate policy uncertainty does not simply delay firms' strategic transformation. Unlike general economic policy uncertainty, climate policy uncertainty contains a clearer long-term orientation toward low-carbon transition. Firms may therefore interpret rising climate policy uncertainty as a signal of future regulatory tightening and respond by accelerating intelligent transformation. From a socio-technical systems perspective, corporate industrial intelligence can be understood as an adaptive technological response through which firms improve efficiency, flexibility, and regulatory adaptability under external institutional disturbance.

Second, the mechanism analysis shows that this effect operates through two resource reconfiguration pathways. The opportunity effect indicates that climate policy uncertainty increases R&D investment, enabling firms to build technological options and prepare for policy-related opportunities. The pressure effect shows that climate policy uncertainty

reduces total factor productivity, exposing the inefficiency of traditional production systems and pushing firms to adopt intelligent technologies to restore efficiency. These findings suggest that corporate industrial intelligence is driven by both proactive opportunity-seeking and pressure-induced adaptation.

Third, the moderating results highlight the role of board-level risk governance as an organizational governance subsystem. Boards with higher educational attainment, stronger innovation orientation, and environmental or risk committees are better able to interpret climate policy signals, evaluate strategic risks, and coordinate resource allocation. As a result, they strengthen the positive relationship between climate policy uncertainty and corporate industrial intelligence. This finding supports the view that board governance connects external institutional uncertainty with internal technological transformation.

Finally, the heterogeneity analysis identified the boundary conditions of this relationship. The effect of climate policy uncertainty was stronger among high-pollution firms, larger firms, and long-established firms. These firms face greater regulatory exposure, possess stronger transformation resources, or have more organizational experience. These findings further suggest that corporate industrial intelligence emerges from the interaction among institutional pressure, governance coordination, resource reconfiguration, and technological upgrading, reflecting a dynamic socio-technical adaptation process.

## 5.2. Limitations and Future Research

This study has several limitations that provide directions for future research. First, although this study measured corporate industrial intelligence using industrial robot penetration and further adopted a text-based alternative measure for robustness checks, corporate industrial intelligence is a multidimensional concept. Our robot-based measure mainly captures the embodied, production-side, and automation-oriented dimension of industrial intelligence, rather than the full scope of Industry 4.0 transformation. Future research may incorporate more detailed firm-level indicators, such as AI applications, industrial Internet platforms, digital twins, IoT, and smart supply chains.

Second, the measurement of board-level governance variables has some limitations. Although this study measured board educational attainment using average years of schooling and further considered STEM educational background, it did not account for university quality or school prestige due to data availability. In addition, our measure of environmental or risk committees only captured whether such a committee formally exists, rather than its activity, expertise, or actual influence on corporate decisions. Future research may use more detailed individual-level and committee-level data to further examine how board governance quality affects corporate technological transformation.

Third, this study focused on industrial intelligence transformation under climate policy uncertainty among Chinese listed manufacturing firms. Therefore, the long-term consequences and contextual boundaries of the findings should be interpreted with caution. Future research may further examine whether such transformation improves firm performance, reduces carbon emissions, or promotes green innovation, and may test the generalizability of the findings across countries, industries, firm types, and technological contexts.

## 6. Conclusions and Implications

### 6.1. Conclusions

Using panel data on 1783 Chinese listed firms from 2011 to 2024, this study examined the relationship between climate policy uncertainty and corporate industrial intelligence from a socio-technical systems perspective, with particular attention to board-level risk governance. The results show that climate policy uncertainty significantly promotes corporate industrial intelligence, and this finding remains robust across a range of tests.

The mechanism analysis shows that climate policy uncertainty promotes corporate industrial intelligence through two pathways: an opportunity effect through increased R&D investment and a pressure effect through reduced total factor productivity. The moderation analysis further shows that board-level risk governance strengthens this relationship. Specifically, the positive effect of climate policy uncertainty is stronger in firms with higher board educational attainment, stronger board innovation orientation, and environmental or risk committees.

The heterogeneity analysis shows that the effect is more pronounced among high-pollution firms, larger firms, and long-established firms. These findings indicate that corporate industrial intelligence is not merely a technological investment decision, but a socio-technical adaptation outcome shaped by external climate-policy uncertainty, internal resource reconfiguration, and board-level governance capacity.

## 6.2. Implications

This study provides several practical implications. First, firms should strengthen their board-level governance for climate-policy uncertainty. Boards need to regularly assess climate policy changes, discuss their implications for technological transformation, and integrate climate-related risks into major investment decisions. Firms may improve their board composition by increasing directors' knowledge of technology, innovation, environmental regulation, and risk management. In addition, environmental or risk committees should not merely remain formal structures; they should be given clearer responsibilities in monitoring climate-policy signals, evaluating transition risks, and supporting intelligent transformation decisions.

Second, firms should improve their climate-risk management by linking external policy uncertainty with internal resource allocation. When climate policy uncertainty rises, managers should not simply delay investment because of unclear policy signals. Instead, they should conduct scenario analysis, evaluate potential compliance costs and transition opportunities, and identify which production processes are most exposed to policy change. This can help firms determine when and where industrial intelligence investment is most needed.

Third, firms should treat industrial intelligence as an organizational adaptation strategy rather than only a technology investment. Intelligent transformation requires coordination among the board, senior managers, R&D departments, production units, and financial departments. Firms should combine R&D investment, digital infrastructure, employee training, and process redesign to ensure that intelligent technologies improve efficiency and flexibility. This is especially important for high-pollution firms, large firms, and long-established firms, which face stronger climate-policy pressure and have greater capacity to undertake system-level adjustment.

Finally, policymakers can support this adaptation process by providing clearer long-term climate-policy signals and targeted support for intelligent and low-carbon transformation. Stable policy expectations, transparent regulatory standards, and incentives for green and intelligent manufacturing can help firms reduce uncertainty and make more forward-looking technological investments.

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## Appendix A

### Appendix A.1

Table A1 presents the detailed definitions of all variables.

**Table A1.** Variable definitions.

| Vars. Abbr.              | Definition                                                                                                                                                                                                                                    |
|--------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <i>II</i>                | Robot-based corporate industrial intelligence, measured by firm-year exposure to industrial robot penetration; it captures the production-side dimension of industrial intelligence.                                                          |
| <i>L.CPU</i>             | One-period lag of the annual city-level Chinese Climate Policy Uncertainty index developed by Ma et al. (2023) [63], matched to the city where the firm is registered.                                                                        |
| <i>R&amp;D</i>           | R&D investment. Natural logarithm of firm R&D expenditure plus 1.                                                                                                                                                                             |
| <i>RD_Intensity</i>      | R&D intensity. Firm R&D expenditure divided by total assets.                                                                                                                                                                                  |
| <i>TFP</i>               | Total factor productivity estimated using the Levinsohn–Petrin approach based on firm-level accounting data from CSMAR.                                                                                                                       |
| <i>Board_Edu</i>         | Average years of schooling of board directors.                                                                                                                                                                                                |
| <i>Board_STEM</i>        | Proportion of board directors with STEM educational backgrounds, calculated as the number of board directors with educational backgrounds in science, technology, engineering, or mathematics divided by the total number of board directors. |
| <i>Board_Innov</i>       | Board innovation orientation. Text-based indicator calculated as the frequency of innovation-related terms in the board report divided by the total word count of the board report, and then min–max normalized to the [0, 1] interval.       |
| <i>Board_EnvRiskComm</i> | Dummy variable equals 1 if the firm has a dedicated environmental committee or a risk committee at the board level in year <i>t</i> , and 0 otherwise.                                                                                        |
| <i>Age</i>               | Firm Age. Natural logarithm of the current year minus the year of incorporation + 1.                                                                                                                                                          |
| <i>Size</i>              | Firm Size. Natural logarithm of the firm’s total assets at year-end.                                                                                                                                                                          |
| <i>Cash</i>              | Net cash flow generated by the firm’s operating activities divided by operating income.                                                                                                                                                       |
| <i>RoA</i>               | The ratio of net profit to total assets.                                                                                                                                                                                                      |
| <i>Lev</i>               | Total liabilities divided by total assets.                                                                                                                                                                                                    |
| <i>RoE</i>               | The ratio of net profit to shareholders’ equity.                                                                                                                                                                                              |
| <i>Audit</i>             | Audit quality. Auditors from the Big Four international accounting firms take 1, otherwise 0.                                                                                                                                                 |
| <i>Top10</i>             | The number of shares held by the top ten shareholders divided by total share capital.                                                                                                                                                         |
| <i>Separation</i>        | Separation of CEO and chair positions. Dummy variable that equals 1 if the CEO and the chairman are different persons, and 0 otherwise.                                                                                                       |
| <i>lngdp</i>             | Natural logarithm of the gross domestic product (GDP) of the city where the firm is registered.                                                                                                                                               |

## Appendix A.2

Table A2 reports the variance inflation factor (VIF) test for the main explanatory and control variables. The maximum VIF was 6.361 and the mean VIF was 2.075, both below the commonly used threshold of 10, suggesting that multicollinearity is not a serious concern.

**Table A2.** Variance inflation factor test.

| Variables         | VIF   | 1/VIF |
|-------------------|-------|-------|
| <i>L.CPU</i>      | 1.013 | 0.988 |
| <i>Age</i>        | 1.448 | 0.691 |
| <i>Size</i>       | 1.265 | 0.790 |
| <i>Cash</i>       | 1.000 | 1.000 |
| <i>RoA</i>        | 6.360 | 0.157 |
| <i>Lev</i>        | 1.010 | 0.990 |
| <i>RoE</i>        | 6.361 | 0.157 |
| <i>Audit</i>      | 1.075 | 0.930 |
| <i>Top10</i>      | 1.245 | 0.803 |
| <i>Separation</i> | 1.030 | 0.971 |
| <i>lngdp</i>      | 1.023 | 0.977 |
| Mean VIF          | 2.075 |       |

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