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Climate policy uncertainty and firm-level total factor productivity: Evidence from China

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ABSTRACT

Using 2605 Chinese A-share listed companies in the mining, manufacturing, and energy production and supply sectors from 2009 to 2020, we examine the relationship between climate policy uncertainty (CPU) and firm-level total factor productivity (TFP). The main findings are as follows: First, CPU significantly reduces firm-level TFP, with a greater impact on low-productivity firms than on high-productivity firms; second, the negative effect of CPU on firm-level TFP is most pronounced for non-state-owned, labor-intensive, and capital-intensive companies; third, CPU hinders research and development investment and reduces the amount of free cash flow. These results indicate that CPU exerts negative impacts on firm-level TFP mainly via its effects on the capital status of the companies. Our findings remain valid after a series of robustness tests and controlling for endogeneity. The government should introduce forward-looking climate policies to reduce the negative impact of policy uncertainty.

1. Introduction

In recent decades, energy consumption has been an important driver of economic development in various countries, and high energy consumption has been associated with strong economic growth (Lee, 2005; Ren et al., 2022b). However, the increase in economic growth has been accompanied by a marked rise in carbon dioxide emissions due to energy dependency on traditional fossil fuels, which has put a huge strain on the environment. To achieve sustainable growth, the utilization efficiency of fossil fuel sources needs to be improved, and there needs to be a shift toward renewable energy (Lee and Chien, 2010). Green finance refers to financial services provided for economic activities that are supportive of environment improvement, climate change mitigation and more efficient resource utilization, and it has attracted attention in many countries as a way to promote sustainable economic growth. Although the development of green finance in China shows an upward trend, the overall level remains relatively low (Lv et al., 2021a, 2021b; Wang et al., 2022; Ren et al., 2022c). Policy makers must take responsibility for reducing carbon dioxide emissions and support the development of green finance. Well-designed and effective policies can promote the economy to grow sustainably (Zhang and Du, 2020).

In modern times, political factors and governance play increasingly important roles in ensuring a sustainable environment (Su et al., 2021). Climate change and excessive carbon dioxide emissions have motivated countries worldwide to participate in climate governance actions (Liu et al., 2020; McCollum et al., 2018; Ren et al., 2022a). Supporting a carbon neutral policy environment is essential to reduce environmental degradation (Ji et al., 2021). Thus far, more than 120 countries have put in place carbon neutrality goals. Uncertainties associated with climate change have prompted governments to formulate corresponding climate policies to regulate industry. Policy-related risks also affect the relationship between energy consumption and economic development (Chiu and Lee, 2020). In particular, climate policy uncertainty (CPU) has major implications for manufacturing and production industries, as it affects production and operation processes. Theoretical studies have assumed an impact of climate change on total factor productivity (TFP) (Dietz and Stern, 2015; Moyer et al., 2014), and there is preliminary empirical evidence for the relationship between the climate change and TFP (Letta and Tol, 2019). Several studies also have investigated the impact of climate change and climate policy on the TFP of different

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industries and different factors (e.g., energy tax) (Gonseth et al., 2015; Sheng et al., 2021). However, there are few studies on how climate policy uncertainty (CPU) affects the TFP of companies. This study aims to examine the effect of CPU on firm-level TFP in China, the second largest economy and largest emerging economy in the world. Specifically, we focus on the impact of CPU on firm-level TFP for the overall sample in mining, manufacturing, and energy production and supply sectors.

We conduct regression analysis using annual data on Chinese A-share listed companies for the period 2009–2020. The results reveal that increased CPU reduces firm-level TFP. Different companies in the sample have different responses to CPU, depending on ownership type and industry type. CPU has a negative effect on the TFP of non-state-owned enterprises (N-SOEs), labor-intensive industries, and capital-intensive industries. Furthermore, CPU reduces TFP by hindering research and development (R&D) investment of companies and reducing free cash flow (FCF), which affect normal production and operation of the firms. In addition, the results of the robustness tests confirm those of the logistic regression analysis.

As the pace of climate change accelerates, so too does the frequency of climate policymaking. The Paris Agreement on Climate Change is the most influential and wide-ranging climate policy globally in the past decade. To further explore the impact of CPU on firm-level TFP, we utilize the Paris Agreement on Climate Change as a policy shock and use the difference-in-difference (DID) model to explore changes in firm-level TFP before and after this policy shock. To balance the covariate differences, we estimate the DID again using a propensity-score-matched (PSM) sample. Both sets of results support our findings that CPU has a significantly negative impact on the firm-level TFP, confirming that CPU hinders firm-level TFP.

This paper contributes to existing research in the following ways. First, this study provides a new perspective for exploring the relationship between climate risk and firm-level TFP. We combine the climate policy uncertainty and a certain policy shock to study the impact of climate risk on firm-level TFP. Policies are needed on various types of industries, and research on the uncertainty of policy caused by climate risk is of greater microeconomic significance than that on the broad economic policy uncertainty (Wen et al., 2022). As a result, our research studying on CPU plays an important role in environmental governance of industries, and its pertinence and feasibility are stronger than universal policies.

Second, this study helps understand the role and impact of policy uncertainty on economic growth. As shown by previous research, TFP is the main driver of economic growth (Santos et al., 2021). The majority of our sample comprises manufacturing industry companies, where TFP directly promotes economic growth (Jia et al., 2020). Understanding how CPU affects firm-level TFP growth can further deepen our understanding of how policy uncertainty affects economic development.

Finally, this study contributes to knowledge on how to improve firm-level TFP in the presence of climate change, thereby enhancing the sustainability of economic development. As a country with a large manufacturing base, the government in China should promote the transformation from a resource- and energy-driven economy to an innovative economy (Chen and Lee, 2020). Improvements in firm-level TFP will enhance the growth of companies, which will improve industry average productivity and thereby promote the sustainable development of both the environment and the economy (Zheng et al., 2009). The findings of this study can help government to implement better climate policies and promote the enhancement of firm-level TFP.

The paper is arranged as follows. Section 2 reviews the relevant literature and presents the research hypotheses. Section 3 presents the data and methods. Section 4 analyzes the empirical regression results and conducts a series of robustness tests. Section 5 further introduces climate policy shocks. The final section concludes the paper.

2. Literature review and hypothesis development

The geography represented by climate is an important factor affecting economic development (Olsson and Hibbs, 2005). In recent years, with the increasing frequency and intensity of extreme weather events, the hazards and risks brought by climate change have attracted attention worldwide. Natural disasters could damage energy consumption and have a profound impact on the production of energy-related industries (Lee et al., 2021a, 2021b). Previous research has shown that damage caused by disasters linked to climate change will affect long-term economic growth via effects on knowledge, not just current outputs (Dietz and Stern, 2015).

In the face of climate change, how to balance economic growth and environmental protection has become an important issue. The government in China has drawn up plans, such as "Made in China 2025", to regulate the production outputs of heavy-polluting companies (Yuan et al., 2020). Today, China's economic development has entered a "new normal" period. Under the new normal, one of the most important changes is a shift from the pursuit of total economic growth to the pursuit of high-quality growth (Hao et al., 2020). In the future, economic growth in China will be more reliant on supply upgrades to drive internal demand than on export of low value products, thereby providing new momentum for endogenous growth. Relevant research shows that, in endogenous growth models, damage to production levels from climate change translates into damage to TFP (Moyer et al., 2014). Thus, climate policymakers need to consider the impact of policies on firm-level TFP.

Due to the complexity of the effect of climate change on the natural environment, no single indicator can be used to measure economic development. TFP represents a combination of labor productivity and capital productivity. It explains total output growth and is an important reference indicator when measuring the growth based on technological progress. In terms of internal factors that improve firm-level TFP, previous research shows that these are mainly R&D investment (Morrow et al., 2010), capital subsidies (Barseghyan and DiCecio, 2011), enterprise scale (Sheng and Song, 2013), and resource allocation efficiency (Chen et al., 2021). In contrast, human capital misallocation has been shown to reduce firm-level TFP (Jia et al., 2020). In terms of external factors that influence firm-level TFP, previous studies report that these are industry regulations, government policies, and market conditions. Among these, market-oriented reforms (Sheng and Song, 2013), policies related to carbon reduction (Chen et al., 2021), and the implementation of green credit policy (Wen et al., 2021; Zhang, 2021) have been shown to enhance firm-level TFP.

In the presence of climate change, the factors affecting the TFP of companies have become more diverse and complex. As mentioned above, the existing literature on factors affecting TFP focuses mainly on the entity level, such as enterprises, governments, and markets, with only a small number of studies addressing the impact of factors at the level of natural environment, such as climate change and climate policy. Unfortunately, there are no studies have considered the uncertainty of climate policy. Thus, the present study examines whether and in what ways CPU affects firm-level TFP.

Under the Chinese-style institution structure, economic growth depends heavily on the frequent promulgation and implementation of policies (Liu et al., 2021). For enterprises, an increase in policy uncertainty will increase decision-making and management costs and ultimately affect production efficiency. At the macro-level, climate change can be expected to exacerbate political instability and reduce industrial production (Arbex and Batu, 2020; Dell et al., 2012). The impact of the risks associated with climate change on economic growth can be expected to be compounded over time, thereby permanently reducing outputs (Letta and Tol, 2019). At the micro-level, climate change is expected to affect the labor supply, capital supply, and production level of companies (Fankhauser and Tol, 2005).

Based on the aforementioned literature, we propose the following hypothesis:

Hypothesis 1. Increased CPU will hinder firm-level TFP.

Climate risk is essentially carbon risk. Policies to deal with climate risk revolve around the issue of how to reduce carbon emissions (Jorgenson et al., 2019). The manufacturing and energy industries are major contributors to carbon emissions. There are many capital-intensive state-owned enterprises (SOEs) in Chinese energy, mining, and manufacturing industries. SOEs are characterized by large scale and guaranteed by national credit, and this is why they usually have extensive financing channels and strong financial strength. In contrast, non-state-owned enterprises (N-SOEs) are likely to be financially constrained (Feng et al., 2020). Compared with SOEs, the impact of environmental changes on cash flow holding is more significant for N-SOEs (Li et al., 2021a, 2021b). Moreover, it is more difficult for N-SOEs to obtain sufficient resources (Pan et al., 2021), thereby making it more difficult to achieve greater economies of scale. As a result, N-SOEs are resilient to risk in the face of external uncertainties, and CPU can be expected to have a greater effect on the TFP of N-SOEs than on SOEs.

According to industry type, firms can be divided into four categories: resource intensive, labor intensive, capital intensive, and technology intensive. The most direct impacts of climate change are its effects on the natural environment, such as temperature (In et al., 2022). Therefore, the impact of climate change and climate policy uncertainty will have a great impact on resource-intensive industries. Capital-intensive industries are usually downstream industries of resource-intensive industries, and they rely on the energy provided by upstream companies. Restrictions on fossil fuel extraction for energy as part of carbon reduction efforts will further affect the level of TFP of capital-intensive industries (Rath et al., 2019; Tugcu and Tiwari, 2016). In contrast to resource-intensive and capital-intensive industries, the TFP of labor-intensive industries depends mainly on labor supply and quality. High temperatures and extreme weather caused by climate change can be expected to have marked impacts on worker productivity (Zhang et al., 2018). Compared with the other three types of industries (i.e., resource intensive, labor intensive, and capital intensive), technology-intensive industries are less affected by climate change and climate policy uncertainty due to their lower dependency on the natural environment and resources.

Therefore, we propose the following hypothesis:

Hypothesis 2. The impact of CPU on firm-level TFP will be heterogeneous among firms, depending on ownership type and industry type.

As mentioned above, climate change may affect TFP through the structure of energy consumption. Technological innovation and the use of renewable energy are effective ways of reducing carbon emission intensity (Wang et al., 2020). By optimizing energy usage and upgrading structure of energy consumption, firm-level TFP can be improved. Given the aforementioned, companies have a strong incentive to invest in R&D to reduce their dependency on traditional fossil fuels and increase their use of renewable energy. Furthermore, due to the increase in climate policy uncertainty and controls on carbon emissions, more companies can be expected to turn to renewable energy as a means to increase TFP (Du et al., 2019). However, increased CPU will simultaneously raise the standard for companies to finance, and it will increase investors' concerns about high-risk investment, making it difficult for companies to obtain sufficient funds to invest in R&D. The latter will ultimately hinder firms from improving their TFP.

In addition, policy-related risks have implications for company decision making on capital allocation (Lee et al., 2021a, 2021b). As the costs associated with coping with uncertainty increase, free cash flow will be reduced. Moreover, CPU will increase capital costs (Drobetz et al., 2018; Xu, 2020), making it more difficult for companies to absorb funds. All these factors can be expected to affect the normal production and operation of companies, thereby affecting TFP.

The above discussion leads to our third hypothesis:

Hypothesis 3. CPU will affect firm-level TFP via its effects on R&D investment and free cash flow.

3. Methods

3.1. Data and sample

We obtain data on CPU index developed by Gavriilidis (2021). This index is used to determine the degree of uncertainty in U.S climate policy changes. Because the United States is the world's largest economy, we can use the U.S CPU index to represent the global climate risk, which also affects China's economy and development. Specific data source can be found on http://www.policyuncertainty.com/climate_uncertainty.html. In 2007, Chinese government published its first National Climate Change Program document. In 2008 and 2009, respectively, the State Council released two white papers on Policies and Actions to Address Climate Change. Combined with the above policies of China and considering the time lag effect of these policies, 2009 is selected as the starting date for this research. CPU index is then averaged by year. Finally, we obtain a total of 12 annual observations from 2009 to 2020.

The sample in this study comprises Chinese A-share listed companies from 2009 to 2020. According to the industry classification categories of the China Securities Regulatory Commission in 2012, the industries comprise companies involved in mining, manufacturing, and energy production and supply. Following the literawture (Fang et al., 2020; Ren et al., 2022; Yang et al., 2019), all the companies' financial information is obtained from the China Stock Market & Accounting Research (CSMAR) Database. To ensure the validity and reliability of the empirical results, we use unbalanced panel data and exclude data with too many missing main variables. To avoid biasing the results due to extreme values, all the continuous variables are winsorized at the 1% and 99% levels. The final sample covers 2605 A-shared listed companies, with a total of 17,323 annual observations.

3.2. Empirical model

This study uses a benchmark model to capture the relationship between CPU and firm-level TFP, and we use a panel regression model with time fixed effects and individual fixed effects. The specification we estimate is as follows:

$$TFP_{it} = \beta_0 + \beta_1 CPU_{t-1} + \beta_2 Size_{it} + \beta_3 Leverage_{it} + \beta_4 ROA_{it} + \beta_5 Growth_{it} + \beta_6 R\&D_{it-1} + \beta_7 EC_{it} + \beta_8 Liquidity_{it} + Year_t + Ind_i + \varepsilon_{it}, \tag{1}$$

where the subscripts i and t refer to the company and year, respectively. TFP_{it} is the natural logarithm of firm-level TFP. CPU_{t-1} is the CPU index. The control variables include a number of enterprise-related properties, including company size ($Size_{it}$), leverage ratio ($Leverage_{it}$), return on total assets (ROA_{it}), revenue growth rate ($Growth_{it}$), investment in R&D ($R\&D_{it-1}$), equity concentration (EC_{it}), and asset liquidity ($Liquidity_{it}$). $Year_t$ is the time fixed effect, Ind_i is the individual fixed effect, and ε_{it} is the unobserved exogenous error term.

3.3. Variables

3.3.1. Firm-level TFP

The dependent variable in this study is TFP. We adopt the LP method (Levinsohn and Petrin, 2003) to calculate firm-level TFP. As the LP method takes intermediate inputs as instrumental variables, this solves the problem of simultaneity bias caused by the simultaneous selection of production and capital stock by companies. Referring to relevant research on the application of LP method (Ackerberg et al., 2015; Li et al., 2021a, 2021b), we take operating income as the output variable, and select net fixed assets and number of employees as capital and labor input variables, respectively. Meanwhile, we use the sum of all costs, excluding depreciation and amortization, as the intermediate input variable.

The Cobb-Douglas production function used in LP method is as follows:

$$y_{it} = \beta_0 + \beta_1 l_{it} + \beta_2 k_{it} + \beta_3 m_{it} + \omega_{it} + \varepsilon_{it}, \tag{2}$$

where y_{it} is the logarithm of firms' output. l_{it}, k_{it}, and m_{it} are the logarithm of labor input, capital input, and intermediate input, respectively. ω_{it} represents productivity shocks which can be observed in each period and affect firms' factor selection in the current period. In contrast, ε_{it} represents shocks to productivity that are not observable and have no impact on firms' input decisions. After getting the estimated results of ω_{it}, we take the natural logarithm of this value. Finally, we obtain the data of firm-level TFP.

3.3.2. CPU

The independent variable in this study is the Climate Policy Uncertainty (CPU) index. In light of increasing climate risks, the frequency of government formulated policies on climate change has also increased. Increased uncertainty surrounding damage caused by climate change has aggravated the uncertainty of climate policy. Therefore, we use CPU index to quantify the extent of climate change. To match the characteristic of other variables, we convert the monthly CPU index into annual data by taking the annual average. To facilitate the reading of coefficient results, we divide the original data by 100 in the regression model.

3.3.3. Control variables

In line with previous research, we control seven variables at the company level thought to affect firm-level TFP, including company size, leverage ratio, return on total assets, revenue growth rate, investment in R&D in the previous period, equity concentration, and asset liquidity. Detailed information on the variables included in the present study is provided in Table 1.

Table 1
Variable definitions.

Variables	Description
Dependent variables	
TFP	Natural logarithm of firm's total factor productivity
Independent variables	
CPU	Climate policy uncertainty index
Treat	Dummy variable of policy change, which indicates the external impact of the agreement
Time	Time index dummy variable, which equals to 1 if observations occurred in 2016 or later; otherwise, 0
Control variables	
Size	Natural logarithm of firm's total assets at the end of the year
Leverage	Ratio of firm's total liabilities to total assets at the end of the year
ROA	Ratio of firm's net profits to total assets
Growth	Revenue growth rate
R&D	Natural logarithm of firm's investment in research and development
EC	Equity concentration measured by the proportion of shares held by the largest shareholder
Liquidity	Current assets divided by current liabilities

3.4. Descriptive statistics

Table 2 reports summary statistics for the variables. The maximum value of TFP at the enterprise level is 11.8, the mean value is 8.986, and the standard deviation is greater than 1, indicating that the average TFP level of the companies included in the study is high despite the large gap between them. The mean CPU index is 1.396, and reaches the minimum value 0.593 and maximum value 2.72 in 2013 and 2020 respectively. As shown in Fig. 1, CPU index shows a rapid upward trend from 2009 to 2020, indicating that the uncertainty of climate policy has increased rapidly during this period.

Table 3 lists the correlation coefficients for the key variables. The correlation coefficient between TFP and CPU is approximately 0.1, and the absolute values of the correlation coefficients of the other variables almost do not exceed 0.5, indicating that there is no serious multicollinearity.

4. Empirical results and discussion

4.1. Baseline results

We use model (1) to explore the effect of CPU on firm-level TFP. The benchmark regression results are shown in Table 4. From the results in the first column, it can be seen that when only time and individual fixed effects are controlled, the coefficient of CPU on the TFP of companies is significantly positive at the level of 1%. However, after the addition of the seven control variables, the coefficient of the CPU index becomes negative, which is significant at the 1% level. These results indicate that the higher the level of CPU, the lower the level of TFP of the companies. From the results in column (8), which includes all the control variables, we can conclude that each unit increase in CPU reduces firm-level TFP by 0.0324 percentage points. The results of the baseline regression model confirm Hypothesis 1, which proposes that increased CPU will impede improvements in firm-level TFP. Thus, the TFP of companies is affected not only by operating capacity and allocation efficiency, but also by the impact of changes in climate policy.

From the results in column (8), which includes all the control variables, it can be seen that the coefficients of corporate size, leverage ratio, return on total assets, revenue growth rate, and asset liquidity are all significantly positive at the level of 1%, which means that companies with large scale, increased profitability and high asset liquidity generally have high TFP. A reasonable explanation for this finding is that companies operating at a large scale have corresponding production, management, and operation processes in place that allow them to improve their production efficiency, even in an uncertain environment (De Mendonca and Zhou, 2020). Similarly, companies with stronger profitability and development capabilities are likely to be able to absorb social investment funds widely, which has a positive impact on the expansion and turnover of total capital, thereby improving their TFP (Xiao et al., 2021). In addition, the higher the liquidity of corporate assets, the faster the assets can be turned into cash, which has implications for companies' responses to external uncertainties and corporate performance (Chang, 2018).

4.2. Heterogeneity analysis

To explore the heterogeneity of the effect of CPU on firm-level TFP, we conduct a subsample regression based on the previous assumptions about impact of CPU on TFP according to ownership type and industry type, and then obtain benchmark model estimation results.

To examine the effect of firm-level TFP on CPU according to ownership type, we divide the companies into state-owned enterprises

Table 2
Summary statistics of variables.

Variable	Observations	Mean	Std.dev.	Min	P25	P50	P75	Max
TFP	17,323	8.986	1.012	6.952	8.275	8.885	9.568	11.800
CPU	17,323	1.396	0.699	0.593	0.848	1.055	1.975	2.720
Size	17,323	21.990	1.202	19.920	21.110	21.810	22.650	25.780
Leverage	17,323	0.399	0.192	0.054	0.246	0.392	0.540	0.869
ROA	17,323	0.038	0.063	−0.257	0.014	0.038	0.069	0.196
Growth	17,206	0.112	0.447	−0.715	−0.125	0.045	0.251	2.327
R&D	17,203	17.820	1.451	13.590	16.960	17.820	18.680	21.650
EC	17,323	34.230	14.250	9.190	23.200	32.140	43.280	73.030
Liquidity	17,323	0.565	0.172	0.143	0.447	0.576	0.695	0.900

This table presents the summary statistics of the variables used in the analysis. All variables are defined in detail in Table 1.

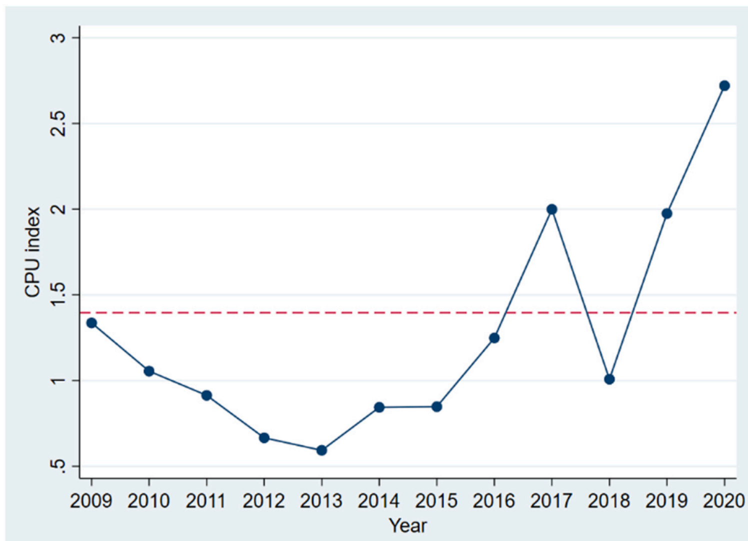

Fig. 1. Average annual CPU index.

Table 3
Correlation coefficients.

Variable	TFP	CPU	Size	Leverage	ROA	Growth	R&D	EC	Liquidity
TFP	1.000								
CPU	0.101***	1.000							
Size	0.844***	0.124***	1.000						
Leverage	0.466***	0.010	0.495***	1.000					
ROA	0.132***	0.009	−0.031***	−0.385***	1.000				
Growth	−0.016***	0.031***	−0.028***	−0.009	0.036***	1.000			
R&D	0.628***	0.176***	0.608***	0.221***	0.116***	−0.004	1.000		
EC	0.185***	−0.079***	0.163***	0.019***	0.137***	−0.008	0.065***	1.000	
Liquidity	−0.052***	0.002	−0.269***	−0.219***	0.178***	0.036***	0.052***	−0.000	1.000

This table shows the correlation coefficients of key variables used for analysis. Variable definitions are explained in detail in Table 1. The symbols ***, **, and* indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

(SOEs) and non-state-owned enterprises (N-SOEs). In the analysis, SOE is the dummy variable, with a value of 1 when the company is state owned and 0 otherwise. The regression results are shown in Table 5. They show that CPU has a more significant negative effect on the TFP of N-SOEs than that of SOEs, that is, CPU poses a greater risk to the TFP of N-SOEs than to that of SOEs. A possible explanation for this finding is credit discrimination by financial institutions. Although banks favor investment in green technology innovation, they are likely to discriminate against companies according to ownership type, which makes it difficult to make full use of resources and hinders improvements in firm-level TFP (Lu et al., 2012; Lv et al., 2021a, 2021b). Faced with increased CPU, SOEs are more likely to be able to obtain funds than N-SOEs. In addition, N-SOEs have an increased risk of financial distress and poor capital turnover, which all have implications for TFP and the ability to respond to CPU. Moreover, when formulating policies, the government is predisposed toward those that favor SOEs, and SOEs have advantages over N-SOEs in terms of access to information on matters of government policies. The policy related risks will further have a negative impact on the financing decisions of N-SOEs (Lee et al., 2021a, 2021b). Thus, as compared with SOEs, in terms of TFP, N-SOEs are more vulnerable to CPU and government policy changes.

Next, we divide the companies into four categories according to the type of industry: resource intensive, labor intensive, capital intensive, and technology intensive. The resource-intensive industries include mining companies and electricity, heat, gas, and water resources production and supply companies. The labor-intensive industries include food processing, textile and apparel, and other commodity manufacturing. The capital-intensive industries consist of

Table 4
Baseline results.

VARIABLES	Dependent variable: Total Factor Productivity (TFP_{it})							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CPU_{t-1}	0.0422***	−0.0084	−0.0089	−0.0142**	−0.0164***	−0.0253***	−0.0261***	−0.0324***
	(6.3685)	(−1.3525)	(−1.4292)	(−2.5070)	(−2.8897)	(−4.2671)	(−4.3138)	(−5.4771)
$Size_{it}$		0.5196***	0.5086***	0.4941***	0.4964***	0.4634***	0.4632***	0.4828***
		(29.4379)	(27.6197)	(28.8415)	(29.2351)	(24.9038)	(24.9760)	(25.7257)
$Leverage_{it}$			0.1516***	0.5559***	0.5476***	0.5408***	0.5416***	0.6087***
			(2.6422)	(10.1505)	(10.0031)	(8.9513)	(8.9864)	(10.2466)
ROA_{it}				2.4747***	2.4386***	2.3090***	2.3159***	2.2033***
				(25.9200)	(26.0775)	(23.7398)	(23.7359)	(23.3378)
$Growth_{it}$					0.0281***	0.0299***	0.0299***	0.0306***
					(4.4151)	(4.3187)	(4.3185)	(4.4990)
$R\&D_{it-1}$						0.0497***	0.0496***	0.0453***
						(5.9522)	(5.9392)	(5.5567)
EC_{it}							−0.0008	−0.0014
							(−0.8303)	(−1.4875)
$Liquidity_{it}$								0.7277***
								(11.7098)
IE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	9.1953***	−2.3742***	−2.1923***	−2.0956***	−2.1429***	−2.2838***	−2.2507***	−3.0113***
	(815.2133)	(−6.0528)	(−5.4443)	(−5.5867)	(−5.7623)	(−6.0215)	(−5.9191)	(−7.8108)
Observations	16,980	16,980	16,980	16,980	16,863	14,250	14,250	14,250
R-squared	0.2925	0.5065	0.5077	0.5887	0.5898	0.5857	0.5858	0.6069

This table shows regression results for the effect of climate policy uncertainty on firm-level total factor productivity. Variable definitions are explained in detail in Table 1. The dependent variable is the natural logarithm of firm-level total factor productivity (TFP), and the independent variable is the climate policy uncertainty index (CPU). The t-statistics are reported in the parentheses. The symbols ***, **, and* indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

Table 5
Heterogeneity analysis based on different types of ownership.

VARIABLES	Dependent variable: Total Factor Productivity (TFP_{it})	
	SOEs	N-SOEs
	(1)	(2)
CPU_{t-1}	−0.0234**	−0.0332***
	(−2.2294)	(−4.6685)
$Size_{it}$	0.4969***	0.4482***
	(12.9869)	(21.1882)
$Leverage_{it}$	0.4168***	0.6394***
	(3.2703)	(9.7856)
ROA_{it}	2.2477***	2.1522***
	(11.1346)	(20.5018)
$Growth_{it}$	0.0260**	0.0311***
	(2.1374)	(3.7991)
$R\&D_{it-1}$	0.0404***	0.0561***
	(3.5470)	(4.8331)
EC_{it}	0.0004	−0.0013
	(0.2714)	(−1.0597)
$Liquidity_{it}$	0.9565***	0.7042***
	(7.5467)	(9.7971)
IE	Yes	Yes
YE	Yes	Yes
Constant	−3.2050***	−2.5047***
	(−4.0461)	(−5.8879)
Observations	4277	9973
R-squared	0.5657	0.6206

This table reports the regression results for the effects of climate policy uncertainty on firm-level total factor productivity considering the ownership type. Variable definitions are reported in Table 1. The t-statistics are reported in the parentheses. The symbols ***, **, and* indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

Table 6
Heterogeneity analysis based on different types of industry.

VARIABLES	Dependent variable: Total Factor Productivity (TFPit)			
	Resources-intensive	Labor-intensive	Capital-intensive	Technology-intensive
	(1)	(2)	(3)	(4)
CPU_{t-1}	−0.0433	−0.0467***	−0.0472***	−0.0133
	(−1.6139)	(−3.6513)	(−4.6723)	(−1.5177)
$Size_{it}$	0.2943**	0.4704***	0.4483***	0.4748***
	(2.5230)	(10.9527)	(18.1325)	(16.2315)
$Leverage_{it}$	0.1530	0.4991***	0.4697***	0.8095***
	(0.3888)	(4.3415)	(5.1489)	(9.2112)
ROA_{it}	2.0453***	2.0448***	2.0148***	2.2734***
	(3.9600)	(9.2853)	(11.3184)	(17.5421)
$Growth_{it}$	0.0155	0.0266	0.0403***	0.0261***
	(0.2995)	(1.5136)	(3.0048)	(3.0493)
$R\&D_{it-1}$	−0.0116	0.0231	0.0399***	0.0734***
	(−0.5232)	(1.4607)	(3.1602)	(4.8356)
EC_{it}	−0.0068	0.0001	0.0014	−0.0031**
	(−0.9671)	(0.0856)	(0.9640)	(−2.2407)
$Liquidity_{it}$	−0.1835	0.7669***	0.7209***	0.7122***
	(−0.4288)	(6.9263)	(6.9969)	(7.1584)
IE	Yes	Yes	Yes	Yes
YE	Yes	Yes	Yes	Yes
Constant	3.3799	−2.2677**	−2.0299***	−3.5214***
	(1.237)	(−2.5436)	(−3.7518)	(−6.4697)
Observations	684	2937	3938	6691
R-squared	0.2533	0.6026	0.5923	0.6336

This table reports the regression results for the effects of climate policy uncertainty on firm-level total factor productivity considering industry type. Variable definitions are reported in Table 1. The t-statistics are reported in the parentheses. The symbols ***, **, and* indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

petrochemicals and metal smelting. The technology-intensive industries include transportation and equipment manufacturing. Table 6 presents the results of the regression analysis, with the sample classified according to production type. As can be seen from the table, CPU exerts negative effects on the different industries to varying degrees. CPU has a great impact on the TFP of resource-intensive industries, and has a little impact on that of technology-intensive industries. We can also find that the negative impact on the labor-intensive and capital-intensive industries is more significant. One possible explanation is that resource-intensive industries are dependent on natural resources. Damage to the natural environment caused by intensification of climate-induced changes will inevitably affect the production activities of resource-intensive industries, thereby reducing their TFP. Unlike resource-intensive industries, the TFP of labor-intensive and capital-intensive industries depends mainly on labor efficiency and capital efficiency, respectively. Thus, the TFP of both types of industries fluctuates more than that of others. For labor-intensive industries, the impact of climate change on the environment, including changes in temperature, combined with CPU, can be expected to have a direct negative effect on worker productivity (Zhang et al., 2018). For capital-intensive industries, the transformation cost of companies with heavy asset equipment is higher than that of others. What's more, increased CPU also has implications for capital-intensive industries in terms of production efficiency, as policy uncertainty can be expected to affect the speed of energy upgrading, thereby placing increased production pressures on these industries (Helms, 2016). As technology-intensive industries are not directly affected by climate change, the negative effect of CPU on their TFP is significantly lower than that of the other three categories.

In conclusion, the negative impact of CPU on firm-level TFP varies according to ownership type and industry type. Among these, N-SOEs, labor-intensive and capital-intensive companies play a more prominent role, providing empirical support for Hypothesis 2.

4.3. Channels analysis

To determine the role of technological progress and capital status in the relationship between CPU and firm-level TFP, we use the BK method (Baron and Kenny, 1986) to construct a mediating effect model. We include R&D investment and free cash flow in a regression analysis as intermediary variables.

First, we assume that increased CPU can affect firms' decision making for technical improvement, thereby affecting firm-level TFP. We use R&D investment (R&D) as an indicator of a firm's technical improvement. The results in column (2) of Table 7 show that the coefficient of CPU for current corporate R&D investment is significantly negative, indicating that CPU hinders R&D investment by companies (Lou et al., 2022). The results in column (3) show that CPU has a significant negative effect on firm-level TFP, whereas R&D investment has a significant positive effect. This finding indicates that the mediating effect of the level of current R&D on firm-level TFP is significant. A reasonable explanation is that an increase in climate risk will prompt countries to strengthen carbon emission standards. Carbon reduction has become an important goal for the sustainable development of mining, manufacturing, and electrical supply industries. From the perspective of subjective motivation, companies will readily invest in R&D and upgrade their production processes in an effort to reduce carbon emissions, as this will not only reduce carbon emissions but improve their energy efficiency, thereby increasing TFP. However, this may not be feasible, as increased CPU can be expected to increase the threshold for companies to obtain funds for R&D (Zhang et al., 2021). Furthermore, societal concerns about high-risk R&D efforts, such as technology innovations, may impede R&D investment. As a result, companies are likely to have insufficient financial capital for R&D to adapt to climate policy uncertainty, thereby hindering TFP.

Second, we also assume that CPU can improve TFP by affecting the capital flows of the firms. Decreased financial constraints and increased cash flow mean more discretionary funds, both of which are conducive to improving TFP. We use free cash flow (FCF) as an indicator of a firm's capital adequacy. As shown by the results in column (5) of Table 7, the coefficient of CPU for companies' FCF is significantly negative, indicating that CPU reduces FCF. According to the results in column (6), CPU has a significantly negative effect on TFP, and FCF has a positive effect

Table 7
Channels analysis through R&D investment and FCF.

VARIABLES	Investment in research and development			Free cash flow		
	TFP_{it}	$R\&D_{it}$	TFP_{it}	TFP_{it}	FCF_{it}	TFP_{it}
	(1)	(2)	(3)	(4)	(5)	(6)
CPU_{t-1}	−0.0324***	−0.0219**	−0.0299***	−0.0324***	−0.0945**	−0.0306***
	(−5.4771)	(−2.1790)	(−5.2123)	(−5.4771)	(−2.1551)	(−3.5298)
$R\&D_{it}$			0.1211***			
			(11.0223)			
FCF_{it}						0.0061**
						(1.9985)
$Size_{it}$	0.4828***	0.4199***	0.4326***	0.4828***	0.7803***	0.5027***
	(25.7257)	(16.7009)	(23.3910)	(25.7257)	(15.1933)	(25.7231)
$Leverage_{it}$	0.6078***	0.1732**	0.5832***	0.6078***	1.8270***	0.7386***
	(10.2466)	(2.4740)	(10.0948)	(10.2466)	(9.6129)	(10.7688)
ROA_{it}	2.2033***	1.3127***	2.0456***	2.2033***	4.0132***	3.2307***
	(23.3378)	(12.1625)	(22.2550)	(23.3378)	(9.9272)	(23.4308)
$Growth_{it}$	0.0306***	0.0417***	0.0256***	0.0306***	−0.0386	0.0270***
	(4.4990)	(3.9206)	(3.9676)	(4.4990)	(−1.1603)	(3.3330)
$R\&D_{it-1}$	0.0453***	0.4213***	−0.0057	0.0453***	0.0489*	0.0443***
	(5.5567)	(18.7758)	(−0.6697)	(5.5567)	(1.8917)	(5.0472)
EC_{it}	−0.0014	−0.0009	−0.0013	−0.0014	0.0006	−0.0012
	(−1.4875)	(−0.6777)	(−1.4610)	(−1.4875)	(0.2193)	(−1.1803)
$Liquidity_{it}$	0.7277***	0.1555**	0.7066***	0.7277***	−2.5709***	0.6611***
	(11.7098)	(2.1362)	(11.5350)	(11.7098)	(−12.4400)	(9.6068)
IE	Yes	Yes	Yes	Yes	Yes	Yes
YE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−3.0113***	1.1291**	−3.1616***	−3.0113***	1.3589	−3.6136***
	(−7.8108)	(2.2097)	(−8.4955)	(−7.8108)	(1.2681)	(−8.7296)
Observations	14,250	14,216	14,216	14,250	9046	9046
R-squared	0.6069	0.5700	0.6257	0.6069	0.1996	0.6640

This table reports the results of the mediator effects of investments in research and development and capital conditions on the climate policy uncertainty's impact on the firm-level total factor productivity. The mediating variables are R&D expenses and free cash flow. Columns (1,2,3) report the results with R&D expenses; Columns (4, 5, 6) show results with free cash flow. Other variables are defined in Table 1. The t-statistics are reported in the parentheses. The symbols ***, **, and* indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

on TFP, indicating that FCF has intermediary effects on the impact of CPU on firm-level TFP. A reasonable explanation for these findings is that an increase in CPU is associated with an increase in the instability of external factors. Most manufacturing and energy companies have high cash reserves to deal with risk (Su et al., 2019). In dealing with uncertainty, company costs increase, which reduces FCF. In addition, CPU makes banks become more cautious in lending, thereby raising the financing threshold. The aforementioned factors can be expected to increase the capital costs of companies and may also reduce FCF. When FCF is reduced, companies cannot fulfill their production potential, which lowers TFP.

In summary, CPU reduces firm-level TFP by hindering research and development (R&D) investment and reducing free cash flow (FCF), which affect normal production and financial status of companies. The conclusion provides empirical support for Hypothesis 3.

4.4. Robustness check

To determine the reliability of the results of the benchmark regression model, we perform a series of robustness tests. To avoid the impacts of the financial crisis in 2008 and the COVID-19 pandemic in 2020, we exclude sample data for 2009, 2010, and 2020 in the regression analysis. Table 8 shows the results for the sample subinterval estimates. The results obtained are highly consistent with those of the baseline model.

The fact that fluctuations in climate policies are generally in response to changes in the natural environment poses a potential endogenous problem in previous analysis. In this study, we use Global Mean Surface Temperature (GMST) data as the instrumental variable to alleviate the effect of endogeneity in a two-stage model regression. The regression results are shown in Table 9. Column (2) shows the estimation results of the first stage of the model. The regression coefficient of the instrumental variable GMST is significant at the 1% level, indicating that there is no problem with weak instrumental variables. Based on the estimation results of the second-stage model in column (3), the coefficient of CPU, the explanatory variable estimated using the instrumental variable, is significantly negative, consistent with the results of benchmark model. In conclusion, our baseline results are valid and reliable.

Table 8
Robustness check with excluding the observations in 2009, 2010, and 2020.

VARIABLES	TFP_{it}
	From 2011 to 2019
CPU_{t-1}	−1.9665***
	(−3.5848)
$Size_{it}$	0.4772***
	(22.1458)
$Leverage_{it}$	0.6243***
	(9.4782)
ROA_{it}	2.1143***
	(19.7801)
$Growth_{it}$	0.0376***
	(4.8376)
$R\&D_{it-1}$	0.0402***
	(4.4703)
EC_{it}	−0.0017*
	(−1.6710)
$Liquidity_{it}$	0.6866***
	(10.1861)
IE	Yes
YE	Yes
Constant	−0.8119
	(−0.9100)
Observations	11,903
R-squared	0.5864

This table reports the results of robustness check with the sample period from 2011 to 2019. Variable definitions are reported in Table 1. The t-statistics are reported in the parentheses. The symbols ***, **, and* indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

Table 9
Robustness check with overcoming endogeneity problems via the 2SLS estimator.

VARIABLES	OLS	2SLS	
	TFP_{it}	CPU_{t-1}	TFP_{it}
	(1)	(2)	(3)
$GMST_t$		3.4365***	
		(87.9300)	
CPU_{t-1}	−0.0324***		−0.0471***
	(−5.4771)		(−2.7757)
$Size_{it}$	0.4828***	−0.0105***	0.6146***
	(25.7257)	(−3.3800)	(103.7242)
$Leverage_{it}$	0.6078***	0.0262	0.9032***
	(10.2466)	(1.6200)	(30.0645)
ROA_{it}	2.2033***	0.0014	2.9340***
	(23.3378)	(0.0300)	(34.6126)
$Growth_{it}$	0.0306***	0.0005	−0.0045
	(4.4990)	(0.1000)	(−0.4673)
$R\&D_{it-1}$	0.0453***	0.0207***	0.0795***
	(5.5567)	(9.1700)	(16.8264)
EC_{it}	−0.0014	−0.0003*	0.0021***
	(−1.4875)	(−1.9500)	(7.1126)
$Liquidity_{it}$	0.7277***	0.0336**	0.8716***
	(11.7098)	(2.1800)	(30.3076)
IE	Yes	Yes	Yes
YE	Yes	Yes	Yes
Constant	−3.0113***	−3.0694***	−6.9402***
	(−7.8108)	(−48.0800)	(−75.8568)
Observations	14,250	14,250	14,250
R-squared	0.6069	0.6915	0.7874

This table reports the results of the robustness check with the 2SLS estimator. Column (1) reports the OLS results. Columns (2) and (3) show the results in second-stage model estimation. Variable definitions are reported in Table 1. The t-statistics are reported in the parentheses. The symbols ***, **, and* indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

5. Further analysis

In the benchmark model regressions, we confirm a significant negative relationship between CPU and firm-level TFP. Climate change affects the choice of production models and technologies, and CPU complicates this process. Meanwhile, we may ignore variables that affect both CPU and TFP, which probably affects the robustness of our conclusions. Therefore, to shed additional light on the impact of CPU due to climate change, we use the Paris Agreement on Climate Change as an exogenous shock and map resulting changes in firm-level TFP.

On 12 December 2015, nearly 200 parties to the United Nations Framework Convention on Climate Change signed the Paris Agreement at the Paris Climate Change Conference. On 3 September 2016, China joined the Paris Agreement on Climate Change, becoming the 23rd party to ratify the agreement. Since then, the Paris Agreement has resulted in the formulation of a range of carbon emission reduction policies (Su et al., 2020). Hence, we choose 2016 as the policy year to study the impact of the agreement on the TFP of Chinese A-share listed companies.

We use the DID method to identify the impact of the agreement on the TFP of the selected companies before and after the policy. The impact of the agreement on firm-level TFP is estimated by the difference in TFP between a treatment group and control group before and after the signing. We rank the companies according to their TFP as low, medium, and high. The low-TFP companies are used as the treatment group, and

Table 10
The effect of the Paris Agreement on Climate Change in 2016.

VARIABLES	Dependent variable: Total Factor Productivity (TFP_{it})			
	DID		PSM + DID	
	(1)	(2)	(3)	(4)
$Time_{it}$	0.6067***	0.1513***	0.5718***	0.1511***
	(28.3348)	(12.3435)	(26.7002)	(11.8146)
$Treat_{it}$	−1.3738***	−0.9623***	−1.3760***	−0.9858***
	(−75.7003)	(−49.3619)	(−76.6463)	(−50.0586)
$Time_{it}$*$Treat_{it}$	−0.0773***	−0.0249**	−0.0595***	−0.0238**
	(−6.1890)	(−2.1607)	(−4.7183)	(−2.0060)
CPU_{t-1}		−0.0212**		−0.0201**
		(−2.3854)		(−2.1986)
$Size_{it}$		0.3308***		0.3030***
		(38.9782)		(34.0268)
$Leverage_{it}$		0.4170***		0.4042***
		(13.0867)		(12.5399)
ROA_{it}		1.7058***		1.7027***
		(30.9051)		(30.0000)
$Growth_{it}$		0.0252***		0.0224***
		(4.4329)		(3.8722)
$R\&D_{it-1}$		0.0311***		0.0327***
		(6.8619)		(6.8357)
EC_{it}		−0.0014***		−0.0013**
		(−2.9589)		(−2.5533)
$Liquidity_{it}$		0.4705***		0.4028***
		(14.1746)		(11.8514)
IE	Yes	Yes	Yes	Yes
YE	Yes	Yes	Yes	Yes
Constant	9.3335***	1.1681***	9.2784***	1.7658***
	(420.1447)	(6.2927)	(418.8064)	(9.0622)
Observations	11,549	9434	10,997	8882
R-squared	0.5789	0.6834	0.5938	0.6818

This table reports the results of the difference-in-differences (DID) approach surrounding the implementation of the Paris Agreement on Climate Change. All variables are defined in detail in Table 1. The t-statistics are in the parentheses. The symbols ***, **, and* indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

the high-TFP companies serve as the control group. After the signing and implementation of the agreement, the TFP levels of companies in treatment group tend to decrease.

The DID regression model we construct is as follows:

$$TFP_{it} = \beta_0 + \beta_1 Treat_{it} + \beta_2 Time_{it} + \beta_3 Treat_{it}{*}Time_{it} + \beta_4 CPU_{t-1} + \beta_5 Size_{it} + \beta_6 Leverage_{it} + \beta_7 ROA_{it} + \beta_8 Growth_{it} + \beta_9 R\&D_{it-1} + \beta_{10} EC_{it} + \beta_{11} Liquidity_{it} + Year_t + Ind_i + \varepsilon_{it}, \tag{3}$$

where *i* and *t* represent the company and year, respectively; TFP_{it} is the natural logarithm of a firm's TFP; $Time_{it}$ is an event dummy variable equal to 1 when an observation occurs in 2016 or later and 0 otherwise; and $Treat_{it}$ is a policy change dummy variable that represents the external shock due to the signing of the agreement. The impact of CPU on firm-level TFP is captured by the DID estimator $Treat_{it}{*}Time_{it}$, as well as time and individual fixed effects.

Table 10 lists the estimation results of model (3). The coefficient of Treat is significantly negative at the 1% level, indicating that CPU hinders TFP. Our focus is on Treat*Time, which measures the impact of CPU on the included firms' TFP following China's accession to the agreement in 2016. The results in columns (1) and (2) show that the coefficient of Treat*Time is significantly negative at the 5% level. Therefore, we conclude that the adverse effect of CPU on firm-level TFP in the treatment group is significantly higher than that in the control group.

Fig. 2 is the dynamic effect test chart of parallel trend. In this chart, the covered short straight line perpendicular to the horizontal axis is the 95% confidence interval of the regression coefficient of each period and the dummy variable of the treatment group. It can be seen that before 2016, the coefficient two years ago is not significant. However, in all years after the implementation of the policy, the coefficient is very significant, indicating that the Paris Agreement has continuous influence, and the impact of the policy is increasing during the sample period.

Next, to further balance the observed covariate differences between the treatment and control groups, we re-estimate the DID using a propensity-score-matched (PSM) sample. We perform one-to-one matching against all the control variables specified in the baseline model, without substitution, and analyze with the common support hypothesis. The regression results are shown in columns (3) and (4) of Table 10. We find that the coefficient of Treat*Time remains negative at the 5% level. The regression results are consistent with the results of general DID estimation, confirming that CPU hinders improvements in firm-level TFP.

6. Conclusions

In the face of increasing climate risks, the government is tasked with formulating policies to deal with CPU. Given that policy uncertainty will affect the profitability and production of companies, this study selects companies in China's mining, manufacturing, and energy production and supply industries to explore the relationship between CPU and firm-level TFP. Based on a sample of Chinese A-share listed companies from

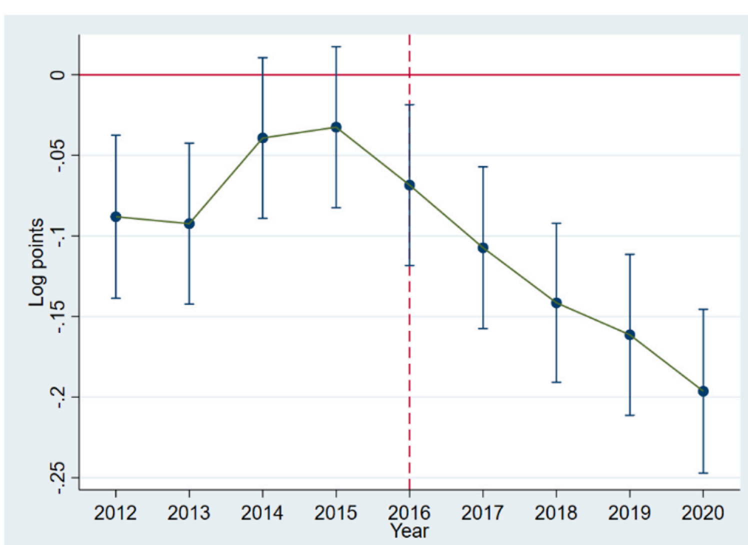

Fig. 2. Total factor productivity of companies in treatment group during 2012 and 2020 (the Paris Agreement on Climate Change was implemented in 2016).

2009 to 2020, we find that CPU significantly reduces firm-level TFP. A series of robustness checks confirm this conclusion. The DID model estimation results that included the policy shock also provide strong support for the research conclusions.

The results also show that CPU has different effects on firm-level TFP with different ownership and production types. Compared with SOEs, N-SOEs are smaller in scale. They have less capital than SOEs and less access to policy information, making them less resilient to risks and more vulnerable to CPU than SOEs. As TFP includes mainly labor efficiency and capital efficiency, productivity fluctuates more in the labor-intensive industries and capital-intensive industries than in the other types of industries. Our empirical results also show that CPU reduces firms' R&D investment and free cash flow, leading to lower TFP. This finding indicates that CPU exerts a negative effect on TFP by imposing constraints on R&D investment and access to funding, which affects the fundamentals of firms and hence further to portfolio selection/management (Zhang and Yan, 2018).

Efficient policymaking has played an increasingly important role in energy conservation and emission reduction (Lee and Chang, 2007). The findings of this study provide important insights into the implementation of better climate policies for the development of companies in mining, manufacturing, and energy production and supply industries. Energy production and energy consumption industries are of great significance in carbon emissions and dealing with climate change risks, and the government should play a major role in improving the TFP of these companies, thereby promoting sustainable development.

This study also provides a new perspective for exploring the relationship between climate change and micro-economic levels. Our results suggest that forward-looking climate policies and substantial government support are vital to ensure that climate policy improves firm-level TFP in the long term. Many countries have formulated policies aimed at developing an environmentally friendly economic. However, failure to maintain policies stability, including putting in place appropriate supportive measures, has significantly reduced the effectiveness of these policies. In the case of CPU, insufficient R&D investment and reduced free cash flow are important factors that hinder TFP. The government needs to focus on how to improve the TFP of companies with low productivity, high costs, and high financing constraints. To reduce the risks associated with CPU and enhance the development of the real economy, the government should also formulate targeted support policies according to characteristics of different industries.

Author statement

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Appendix A. Supplementary data

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