

# **Weathering the Policy Storm: How Climate Strategy Volatility Shapes Corporate Total Factor Productivity**

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**Abstract:** Changes in climate policies have become a critical consideration for businesses, necessitating strategic adaptation and innovation in the face of evolving regulations to achieve long-term success. This study investigates the impact of climate policy uncertainty (CPU) on firm-level total factor productivity (TFP) using a dataset comprising 5,954 North American listed companies from 2000 to 2019. Our findings demonstrate a significant negative relationship between CPU and firms' TFP. Particularly, firms operating in the secondary sector, with higher credit ratings, smaller Tobin's Q, and greater profitability, experience more significant negative effects from CPU. The mechanisms through which CPU operates include cost escalation, reduced turnover, and constrained investment. Employing the Local Projection Instrumental Variable (LP-IV) method, we observe that the relationship between CPU shocks and firm-level TFP is time-varying. The adverse effect of CPU on TFP is most severe in the third year following the occurrence of the shock. To mitigate the negative consequences, governments should enhance the continuity and foresight of climate policies, while firms need to effectively identify and manage climate risks to bolster their resilience in the face of uncertainty.

**Keywords:** Climate policy uncertainty; Total factor productivity; Heterogeneous impacts; Influence mechanism

## 1. Introduction

Climate change is intricately connected to human survival, and its phenomena and impacts have become a pressing concern for the international community (Abbass et al., 2022). In the last few years, the occurrence of extreme heat and drought in numerous countries worldwide has significantly disrupted agricultural production, people's livelihoods, and socioeconomic development (Shivanna, 2022). The Intergovernmental Panel on Climate Change (IPCC) has repeatedly emphasized in its Global Climate Assessment Report that the world is facing an impending climate

change crisis, urging countries to expedite their efforts in reducing carbon emissions. To effectively address the rapidly deteriorating climate change problem and ensure environmental and energy sustainability, proactive policy instruments are indispensable.

However, it is important to acknowledge that the presence of climate policy uncertainty can significantly influence the overall performance of society (Fuss et al., 2009; Ren et al., 2023). Frequent and uncoordinated climate policies give rise to the fallacy of synthesis. In addition, economic agents face considerable challenges in precisely forecasting if, when, and in what manner governmental bodies might alter existing policies, thereby engendering a state of uncertainty regarding climate policy (Mayer, 2002). For instance, the Paris Agreement, signed by over 170 countries worldwide in 2016, marked a significant milestone in the fight against climate change, establishing a unified framework for global climate governance beyond 2020 (Dimitrov, 2016). However, the widespread COVID-19 pandemic, military conflicts, and social crises may lead to a reduced focus on environmental protection and climate policy. This has brought about uncertainty regarding the future of global climate politics and governance (Dupont et al., 2020).

Uncertainty in economic policies and its impacts have long been investigated, such on market prices (Wang et al., 2014), investment (Rao et al., 2017), cost of capital (Xu, 2020) and exports (Qi et al., 2020). In particular, at the firm level, studies by Lee and Chang (2007), Ioannou and Serafeim (2012) and others demonstrate that national-level institutionalized characteristics significantly influence the sustainability performance of firms. Concurrently, as an inherent outcome of the implementation of economic policies, uncertainty assumes a pivotal role in influencing micro-level firm behavior.

In addition, an extensive array of research has explored the impacts of climate change on both economic development and firm operations (Diaz and Moore, 2017; Auffhammer, 2018). Furthermore, the impact of climate change on total factor productivity (TFP) in agriculture, urban areas, and other domains has garnered significant attention from scholars as well. (Liang et al., 2017; Zhang et al., 2018; Chen and Gong, 2021). However, there is a relative scarcity of studies specifically focusing on the influence of climate policy uncertainty (CPU) on firms' TFP. Thus, by merging the characteristics of both areas, it can be inferred that CPU may ultimately influence firm performance by affecting decision-making processes and production operations.

This study offers valuable insights into the effects of CPU on firm-level TFP, utilizing micro-level data from publicly listed firms in North America from 2000 to 2019. Firstly, the empirical results demonstrate a clear and statistically significant negative relationship between increasing CPU and firms' TFP. Secondly, this negative effect of CPU varies across industries, credit ratings, and firm values. In comparison, the impact of CPU on the secondary industry, higher credit ratings, lower Tobin's Q and stronger profitability companies is more intense. Thirdly, an escalation in CPU tends to elevate firms' selling, general, and administrative expenses, as well as finished goods inventory, while leading to a decrease in acquisitions and capital intensity, ultimately resulting in reduced TFP. In the further analysis, the Local Projection Instrumental Variable approach is used to explore the influence of CPU on TFP from a dynamic perspective. A series of comprehensive robustness tests have been performed to affirm the reliability of these conclusions.

This paper contributes three significant advancements to the existing literature. Firstly, it adds to the understanding of the socioeconomic implications of climate

policies, particularly at the micro level. Most existing studies have primarily focused on its macro-level implications for ecological and agricultural development (Pollitt et al., 2015; Fried, 2018). In fact, it will also affect micro-entities of the economy through a variety of mechanisms. Therefore, our study places greater emphasis on the microeconomic ramifications of climate policy by investigating the influence of CPU on firms' TFP.

Furthermore, the outcomes of this research bear significant implications for the development and refinement of climate policies. The empirical findings verify that climate policy uncertainty obviously threatens the productivity level of firms, and this relationship is time-varying. When crafting climate policies, policymakers should prioritize the continuity and stability of these policies. Striking a balance between environmental enhancement and economic growth is vital, ensuring that the expansion and progress of firms are not unduly compromised in the pursuit of environmental governance.

Lastly, this study assists firms in understanding how to enhance their TFP in an environment of uncertainty. Various risks, including CPU, cast a shadow over the company's future growth (Darby et al., 2020). However, potential economic benefits should also be acknowledged. Both domestic and international investors are placing more importance on firms' environmental and climate responsibilities. A robust ability to manage climate risks and outstanding ESG performance can create new opportunities for financing (Fatemi et al., 2018). Therefore, firms should expedite their transformation processes and proactively integrate climate risk-related management into their daily operations to achieve long-term sustainable development.

The structure of this study is organized as follows: Section 2 compares prior studies relevant to our research topic and presents our hypothesis regarding the influence of CPU on TFP. Section 3 provides details on the data and constructs an empirical model. Section 4 presents the empirical findings and robustness tests conducted by various methods. Section 5 delves further into the shocks stemming from changes in climate policy. Finally, Section 6 summarizes the conclusions derived from above investigation.

## **2. Literature review and hypothesis development**

Over the past few years, the intensifying concerns about climate change have garnered considerable global attention, as highlighted by Qureshi et al. (2013). Discussions regarding climate change typically conjure images of extreme meteorological events, escalating temperatures, and the looming peril of species extinction. Moreover, climate change significantly results in the deterioration of air quality and the increased prevalence of infectious diseases, posing direct threats to human health, as detailed by McMichael et al. (2006). As a pivotal issue impacting human existence, climate change inflicts severe damage to the ecological environment and exerts a profound influence on socio-economic development across various sectors, including agriculture and tourism, as noted in studies by Bigano et al. (2008) and Piao et al. (2010).

In response to these challenges, governments must proactively address climate change. In November 2018, the European Union took the lead in the effort to "build a carbon-neutral continent." In September 2020, China set clear objectives to achieve "carbon peaking" by 2030 and "carbon neutrality" by 2060. It is evident that low-

carbon transformation has become a strategic choice embraced by the international community in tackling climate risks (Zhao et al., 2022). Major global economies are promoting low-carbon development through technological innovation and transitioning their energy structures. But the country's move towards carbon neutrality must not come at the expense of economic development. Moyer et al. (2014) remind that climate change directly impacts productivity, as evidenced by the harm inflicted on TFP. Consequently, policymakers must take the micro impact of policies into consideration.

TFP serves as a crucial measure of productivity, representing the overall efficiency of a production unit and its internal factors. Numerous studies have examined the factors influencing a firm's TFP. Internal factors include ownership structure (Ren et al., 2022b), investment in research and development (Engelbrecht, 1997) and organizational orientation (Francesco et al., 2012). External factors, such as corporate tax rates (Bournakis and Mallick, 2018), gender structure (Tsou and Yang, 2019), and policy distortions (Ranasinghe, 2014), also play significant roles. Research on the impact of climate policy on firm-level TFP remains sparse, and the topic of climate policy uncertainty remains largely unexplored. Consequently, this paper endeavors to scrutinize both the extent and the mechanism in which CPU influences firm-level TFP.

Policy uncertainty exerts a considerable influence on the production operations of firms, as evidenced by the findings of Qi et al. (2020). The study by Cai and Ye (2020) further reveals that the enactment of China's new environmental protection legislation has led to a significant reduction in companies' TFP. Policy uncertainty stemming from changes in regional leadership can increase firms' tax avoidance behavior (Yu et al., 2021) and significantly reduce their investment in the current year

(Jia et al., 2013). According to real options theory, uncertainty in the external environment can impede firms' long-term investments, including investments in sustainable development. As one of the most significant external uncertainties, policy changes are likely to impose additional costs and expenses on firms, leading to increased financing costs and ultimately disrupting their productivity (Gulen and Ion, 2016; Jia and Li, 2020; Wen et al., 2022). Moreover, climate variations can also impact firms' production schedules and labor supply, among other factors.

Based on these observations, we propose the first hypothesis in our study:

**Hypothesis 1:** *An increase in CPU will lead to a decrease in TFP at the firm level.*

Different types of companies may respond differently to climate policy uncertainty due to their specific industry attributes. Climate change directly affects the natural environment, including temperature, soil, and water resources, and in severe cases, it can trigger natural disasters (Short and Neckles, 1999; Arnell, 2004; Li et al., 2023; Ren et al., 2024). Therefore, certain industries may be more susceptible to direct impacts of climate changes and climate policies, such as energy-intensive or high-carbon-emitting industries, which could face greater adjustment pressures and cost increases (Farrell and Lyons, 2016; Wang et al., 2024). Conversely, certain industries might experience benefits from the advancement of climate policies, particularly those associated with low-carbon economies or renewable energy sectors (Shang et al., 2022). Therefore, companies in different industries may generate different responses in the face of climate policy uncertainty.

The effects of climate policy changes also transmit to capital markets. Fuss et al. (2008) pointed out that investors face not only the uncertainty brought by traditional market price fluctuations but also the unimaginable uncertainty brought by more

stringent climate change policies. ESG and climate-related information have become crucial decision-making factors for investors in the investment process (Wen et al., 2021). Wang et al. (2021) found that changes in climate policy led to adjustments in bank loan pricing models, and market investors become more cautious. Additionally, a company's market performance and profitability are also important factors that influence its ability to attract capital favor and cope with policy risks.

Accordingly, we propose our second hypothesis:

**Hypothesis 2:** *The influence of CPU on the TFP of various firm types is expected to exhibit heterogeneity, depending on factors such as their industry type, market performance, and profitability.*

Alterations in climate policies are likely to increase firms' operating costs (Xu, 2020). For instance, stricter emission standards may require firms to purchase suitable treatment equipment and hire professionals to conduct assessment tests. These actions entail significant capital investment and resource allocation, posing challenges for firms. Moreover, the uncertain environment complicates sales efforts, resulting in increased inventory accumulation in warehouses and difficulties in maintaining cash flow, which, in turn, is expected to impede firms' TFP.

Policy uncertainty also affects firms' capital allocation decisions (Rao et al., 2017; Golub et al., 2018). As mentioned earlier, firms face increased financing and operating costs, as well as reduced cash flows in the face of high climate risk. Out of caution and due to constrained cash flows, firms are likely to scale back their acquisition investments and reduce certain capital expenditures. According to the "pollution haven hypothesis" put forth by Walter and Ugelow (1979), it is posited that certain highly polluting industries may relocate across international borders to

circumvent stringent environmental regulations. Lower capital intensity ultimately results in a decrease in TFP for the firm.

In summary, we propose our final hypothesis:

**Hypothesis 3:** *The mechanisms by which an increase in CPU leads to a decline in firm-level TFP include rising costs, decreased efficiency, and reduced investment.*

### 3. Research design

#### 3.1. Data and sample selection

We utilize the Climate Policy Uncertainty (CPU) Index developed by Gavriilidis (2021) to capture the level of uncertainty surrounding climate policy changes in the United States. This index is constructed based on the analysis of relevant articles obtained from eight prominent US newspapers.

For our study, we focus on the sample period from 2000 to 2019, as this timeframe provides a comprehensive overview of how climate policy uncertainty impacts firms' performance. Financial data for all firms are sourced from the Compustat database. We combine the datasets and eliminate any missing values, concurrently applying a 1% trim on both ends of the distribution of continuous variables, with the aim of attenuating the impact of extreme values on our regression outcomes. Ultimately, the refined dataset encompasses 45,441 annual observations derived from 5,954 firms. The detailed explanation of main variables is presented in Table 1.

Table 2 presents the descriptive statistics for the final sample. The firm-level TFP exhibits a substantial range, with its apex at 3.321 and nadir reaching -5.9834.

This disparity highlights the significant variation in productivity across firms. The CPU index demonstrates an upward trend starting from 2000 and reaches its peak in 2020, displaying a value nearly 10 times higher than that in 2000. This substantial increase reflects the rapid growth of climate policy uncertainty in recent years. The remaining variables also vary widely between firms.

Table 3 provides the correlation coefficients between two of the key variables, while Figure 1 visually represents these correlations. The correlation coefficient between CPU and TFP is less than 0.01, while the absolute values of other correlation coefficients fall below 0.6. It indicates a lack of severe multicollinearity among the variables.

*Insert Table 1 & Table 2 & Table 3*

*Insert Figure 1*

### **3.2. Variables**

#### **3.2.1. Dependent variable - firm-level total factor productivity (TFP)**

We choose total factor productivity as the proxy measure for firms' productivity levels. TFP is the ratio of total production to total factor inputs. Owing to its encompassing nature, TFP is frequently utilized as a benchmark to evaluate the quality of economic development and the production performance of firms.

The semi-parametric approaches developed by Olley and Pakes (1996) and Levinsohn and Petrin (2003), widely known as the OP method and the LP method, respectively, are extensively employed for estimating the parameters of the aforementioned production function. The LP method enhances the OP method by resolving the issue of sample attrition through variable substitution. Utilizing

intermediate input as a surrogate for investment, the LP method curtails sample loss and efficaciously addresses endogeneity issues, thereby yielding consistent and efficient estimates of input factors. Consequently, our study adopts the LP method for the measurement of firm-level TFP.

Based on pertinent scholarly studies investigating the utilization of LP method, specifically the works of Akerberg et al. (2015) and Li et al. (2021a, 2021b), operating income is designated as the dependent variable. Furthermore, net fixed assets and the number of employees is identified as the independent variables symbolizing capital and labor inputs, respectively. Cumulative costs, excluding depreciation and amortization, are employed as the proxy for intermediate input. The LP method utilizes the Cobb-Douglas production function of the following form:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \omega_{it} + \eta_{it} \#(1)$$

where the dependent variable  $y_{it}$  represents the natural logarithm of firm i's value added in period t.  $l_{it}$ ,  $k_{it}$  and  $m_{it}$  denote the natural logarithms of inputs of labor, capital, and intermediate goods and services, respectively.  $\omega_{it}$  stands for the productivity level, and  $\eta_{it}$  represents the error term, which is unobservable to both the firm and the econometrician. After obtaining the estimated values of  $\omega_{it}$  we take the logarithm to derive the values of firm-level TFP.

In the robustness test, we incorporate an additional method for calculating TFP proposed by İmrohoroglu and Tüzel (2014). On the basis of the OP approach, this method allows us to obtain firm-level TFP once we obtain parameter estimates  $\widehat{\beta}_0$ ,

$\widehat{\beta}_l, \widehat{\beta}_k$  and  $\widehat{\beta}_m$  for the production function. The formula for computing logarithm of TFP is as follows:

$$\omega_{it} = y_{it} - \widehat{\beta}_0 - \widehat{\beta}_l l_{it} - \widehat{\beta}_k k_{it} - \widehat{\beta}_m m_{it} \#(2)$$

In this estimation, industry-specific time dummies are included, ensuring that the results remain uninfluenced by either industry-specific or aggregate TFP fluctuations in any particular year. Furthermore, İmrohoroglu and Tüzel (2014) provide further evidence of the close relationship between firm-level TFP and various firm characteristics, including size, book-to-market ratio, and hiring rates.

### 3.2.2. Independent variables - climate policy uncertainty (CPU) Index

Our research focuses on analyzing the influence of climate policy uncertainty on firm-level TFP. Given the increasing severity of climate change, sectors related to climate risks are witnessing faster development of climate policies. The formulation and adjustment of climate policies present a complex challenge, encompassing multiple domains such as energy, economy, and the environment. These policies exert significant influences on various aspects of economic development.

To measure the impact of climate policy uncertainty on TFP, we adopt the CPU index as our independent variable. The CPU index is calculated monthly, while the other variables in our study are collated annually. To align the data, we compute the annual CPU index by averaging the monthly indices for each year. The CPU index serves as an indicator of the level of uncertainty in climate policy, where higher values represent greater uncertainty. As shown in Figure 2, the CPU index showed a fluctuating upward trend during the sample period. To enhance the interpretability of

the regression model's coefficient results, we take the natural logarithm of the CPU data.

*Insert Figure 2*

### 3.2.3. Control variables

To account for the influence of additional firm characteristics on TFP, we incorporate a comprehensive set of seven control variables. These variables include firm size, leverage, return on equity, current ratio, asset tangibility, earnings per share, and cash flow. By including these variables, we aim to capture various aspects of the firm's characteristics and capabilities that may impact TFP. Table 1 details the meanings and measures of the variables involved in this paper.

### 3.3. Empirical model

We employ a benchmark regression model to capture the relationship between CPU and firm-level TFP. The model incorporates both time fixed effects and individual fixed effects, allowing us to account for time-specific factors as well as firm-specific characteristics:

$$TFP_{it} = \beta_0 + \beta_1 CPU_t + \beta_2 Size_{it} + \beta_3 Lev_{it} + \beta_4 ROE_{it} + \beta_5 Liquidity_{it} + \beta_6 Tangibility_{it} + \beta_7 EPS_{it} + \beta_8 CF_{it} + Year_t + Ind_i + \varepsilon_{it} \quad (3)$$

where the subscripts  $i$  and  $t$  represent the firm and year, respectively.  $CPU_t$  is the natural logarithm of the annual CPU index value. There are seven control variables, namely, firm size ( $Size_{it}$ ), leverage ( $Lev_{it}$ ), return on equity ( $ROE_{it}$ ), liquidity ( $Liquidity_{it}$ ), tangibility of assets ( $Tangibility_{it}$ ), earnings per share ( $EPS_{it}$ ), and cash

flow ( $CF_{it}$ ).  $Year_t$  represents time fixed effects and  $Ind_i$  represents individual fixed effects.  $\varepsilon_{it}$  is the unobserved exogenous error term.

## 4. Empirical results

### 4.1. Baseline results

We employ model (4) to examine the impact of CPU on firms' TFP by sequentially adding each control variable. The regression results are presented in Table 4. In the first column, even when controlling for time and individual fixed effects alone, the effect of CPU on firms' TFP is already significantly negative. The inclusion of additional control variables does not alter the significance level.

Upon the inclusion of all control variables, the coefficient for the effect of CPU on firm's TFP is -0.1403, which remains significant at the 1% level. This finding supports hypothesis 1, suggesting that an increase in CPU impedes the growth of firm-level TFP. The uncertainty surrounding climate policies has a crucial impact on firms' productivity. firms not only need to focus on improving product quality, technological efficiency and management practices, but also closely monitor the fluctuations and impacts of climate policies during their operations.

The complete regression results in column (8) reveal significant positive coefficients at the 1% level for firm size, EPS, and cash flow. This indicates that larger firms with stronger profitability and ample cash flow tend to exhibit higher TFP. This observation is reasonable as larger firms often possess more comprehensive and systematic production and operational processes, enabling them to better withstand uncertainty and maintain their productivity levels. In contrast, changes in climate policies may lead to increased credit risks and loan costs (Wang et al., 2014). firms

with robust profitability and asset liquidity are more likely to gain investors' trust, attract funding in uncertain market environments, ensure smooth capital turnover, and provide financial security for enhancing productivity.

*Insert Table 4*

#### **4.2. Endogeneity test**

There may be endogeneity issues in our main analysis. Firstly, there may exist a reverse causality problem between CPU and TFP. The emissions of pollutants such as carbon dioxide and sulfur dioxide by firms in their production processes are significant contributors to climate change, exacerbating environmental pressures and leading to the implementation of climate change policies by governments, thus increasing climate policy uncertainty. Secondly, there may be omitted variable issues in the baseline regression. Therefore, we employ the two-stage least squares (2SLS) estimation method to address endogeneity concerns.

We select the logarithm of carbon dioxide emissions (measured in million tons) in the United States as the instrumental variable. Given that climate policy primarily aims to address the climate change issues caused by global warming, excessive carbon dioxide emissions are considered a primary culprit behind global warming. Reducing carbon dioxide emissions is the central goal of climate policies, hence climate policy uncertainty is highly correlated with carbon dioxide emissions. At the same time, it is unlikely that national-level carbon dioxide emissions would directly affect firms' productivity levels and financial indicators. Therefore, this instrumental variable satisfies the requirements of relevance and exogeneity. Table 5 presents the results of the 2SLS estimation, and the coefficient of CPU remains significantly negative. This indicates that our results remain robust and reliable after considering

the impact of endogeneity. In addition, the absolute value of the coefficient corresponding to CPU increases compared with the baseline regression result, suggesting that the potential endogenous problem has led to an underestimate of the negative impact of CPU on firm-level TFP.

#### *Insert Table 5*

### **4.3. Heterogeneity analysis**

In order to test Hypothesis 2 and explore the differential impact of CPU on TFP across different types of firms, we further divided the sample into groups and conducted separate regression analyses. Our grouping criteria consisted of four categories: industry type, Standard & Poor's rating, Tobin's Q, and profitability.

Firstly, firms in different industries exhibit significant variations in their business scope and developmental characteristics (Cai et al., 2016). NAICS is a business classification system that categorizes firms into different industries based on similar or identical production processes (Kelton et al., 2008). According to the NAICS codes, we classified firms into three categories: primary industry, secondary industry, and tertiary industry. The regression results in Table 6 demonstrate a significant negative impact of CPU on TFP for firms in all industries. The negative effect is strongest for the secondary industry, while the tertiary industry experiences a relatively weaker impact. The effect on primary industry companies is only significant at the significance level of 10%, which is slightly weaker than the other two categories.

The secondary sector typically involves activities related to energy consumption, emissions, and resource utilization, which is closely tied to climate-related activities. These industries often rely more heavily on energy and natural resources such as oil, coal, and water resources (Bassi et al., 2009). Therefore, changes in climate policies

can lead to issues such as rising energy prices and unstable resource supply, which may have a more direct and significant impact on the operations and production methods of these industries. In contrast, the tertiary sector is more focused on services, retail, and entertainment, relying more on human resources and technological innovation, with relatively lower demand for energy and natural resources (Doytch and Narayan, 2016). Consequently, it exhibits lower sensitivity to climate policies and thus experiences relatively smaller negative impacts.

***Insert Table 6***

Furthermore, Standard Poor's credit ratings provide a relatively objective and accurate reflection of the debt-paying capacity and willingness of governments, firms, and other institutions, attracting widespread attention from global investors (Livingston et al., 2010). We generated a dummy variable, Qua, based on the rating results, with a value of 1 for firms rated A or B, and 0 for firms rated C or D. The results are presented in Table 7. The coefficient for the former is larger than that for the latter, and both coefficients are significant at the 1% level. This indicates that an increase in CPU exerts a significant adverse impact on both groups of firms' TFP. Surprisingly, firms with better credit ratings experience a greater impact.

A possible explanation for this is that firms with better credit ratings often have higher investment levels and more complex global supply chain networks, which may involve a greater amount of fixed assets and technological innovation (Al-Najjar and Elgammal, 2013). Changes in climate policies can disrupt various links in the supply chain, such as restricted raw material supply and increased transportation costs, necessitating larger-scale adjustments and transformations for these firms. Additionally, changes in climate policies can alter the market dynamics within

industries, such as the emergence of new low-carbon technologies and products, which may impact existing market shares and profitability (Ward et al., 2019). As firms with better credit ratings hold a more prominent position in the market, they may be more susceptible to the negative effects of such market changes.

***Insert Table 7***

Tobin's Q is defined as the ratio of a firm's market value to its replacement cost and is one of the most important indicators for measuring firm performance or growth (Wolfe and Sauaia, 2003). Given that the replacement cost of a firm's assets signifies their intrinsic value, and the market value of its stocks represents investor evaluations in the market, it is posited that a Tobin's Q ratio greater than 1 indicates a firm's overvaluation in the financial market, whereas a ratio less than 1 suggests undervaluation. We divide the sample into two groups based on the Tobin's Q values of each firm, using 1 as the threshold, and obtain the regression results as shown in Table 8. In comparison, an increase in CPU exerts a more pronounced negative impact on firms with Tobin's Q values less than or equal to 1.

Firms with Tobin's Q values less than or equal to 1 are generally considered to be undervalued in the market and may face more uncertainty and risk from the capital market. When climate policies change, investors may have greater concerns about the future profitability and market prospects of these firms (Mirza et al., 2022). Additionally, firms with Tobin's Q values less than or equal to 1 may face constraints on capital investment because a market value lower than the net value of assets implies that the firm may struggle to obtain sufficient funds for innovation and transformation. On the other hand, firms with Tobin's Q values greater than 1 already have market values higher than their net asset value, making them more capable of

capital investment and better equipped to address the challenges brought about by climate policy changes (Chiang and Lin, 2007).

***Insert Table 8***

Finally, the firms are divided into two groups based on their profitability. Profitability is measured using the net profit margin, which is the net profit divided by the main operating revenue. The results in Table 9 suggest that firms with higher profitability actually experience a greater negative impact, and the difference is significant.

One possible explanation is that firms with higher profitability are concentrated in financial institutions and non-essential consumer goods production firms. Climate change has the potential to significantly impact a firm's cash flow and balance sheet, leading to increased credit risk and liquidity risk for financial institutions (Dai and Zhang, 2023). At the same time, policies aimed at addressing climate change and promoting a low-carbon economy, such as sudden tightening of carbon emissions, can pose repricing and transformation risks for high-carbon assets (Karydas and Xepapadeas, 2022). According to the precautionary savings theory, under conditions of future uncertainty, individuals choose to increase savings and reduce consumption to mitigate uncertainty, starting with cutting back on non-essential consumer goods (Carroll and Samwick, 1998).

Additionally, firms with higher profitability are often subject to higher market expectations and investor attention. When climate policies change, investors may pay closer attention to the sustainability and environmental impact of these firms, making them more sensitive to changes in their profitability (Reboredo and Ugolini, 2022). If firms cannot effectively respond to climate policy changes, they may face negative

evaluations from investors and pressure from the capital market, leading to increased financing constraints and decreased productivity (Venturini, 2022). Therefore, firms with currently higher profitability may be more susceptible to the impact of CPU on their TFP.

***Insert Table 9***

In summary, the impact of CPU on a firm's TFP varies depending on its industry type, credit rating, market performance, and profitability, thus validating Hypothesis 2. Among them, firms in the secondary industry, with higher credit ratings, lower Tobin's Q, and higher profitability, are more affected by CPU. Therefore, these types of companies should place greater emphasis on identifying and responding to climate risks and related policy changes.

***Insert Figure 3***

#### **4.4. Mechanism analysis**

TFP reflects the overall productivity of a firm as a production system under various input factors. In order to identify the specific pathways through which CPU affects a firm's TFP, we employ the Baron and Kenny (1986) approach to construct the mediation model and introduce four mediating variables: (1) Selling, General, and Administrative Expenses (SG&A); (2) Finished Goods Inventory (Invfg); (3) Acquisitions (Aqc); (4) Capital Intensity (Capiin). These variables comprehensively cover a firm's production, operational, and financing activities. The complete results are summarized in Table 10.

The results in the second column show that the coefficient of CPU on SG&A is significantly positive at the 1% level, indicating that an increase in CPU leads to an increase in a firm's operating costs. In the third column, the coefficient of SG&A on the firm's TFP is significantly negative, suggesting that SG&A plays an important mediating role, and the increase in CPU reduces TFP by increasing SG&A costs. The analysis suggests that this may be due to the changing climate policies, such as the Carbon Border Adjustment Mechanism (CBAM) implemented by the European Union in October 2023, which imposes high requirements on a firm's carbon emissions accounting (Zhao et al., 2023). This requires firms to allocate a significant amount of funds to purchase corresponding environmentally friendly equipment and hire professionals for assessment and inspection, resulting in additional costs (Zhang et al., 2022).

Similarly, combining the results from the fourth and fifth columns, we can conclude that finished goods inventory also plays a significant mediating role. An increase in CPU may lead to changes in market demand and preferences, such as a preference for environmentally friendly products and those that disclose their carbon footprint (Armenio et al, 2022; Norouzi et al., 2022). In such cases, sales become more challenging, resulting in an increase in the backlog of finished goods in warehouses, a decrease in turnover rate, hindering the recovery of cash flow, and having a negative impact on the firm's TFP.

Furthermore, the regression results with acquisitions and capital intensity as mediating variables are shown in columns six to nine. Capital intensity is the ratio of capital expenditure to total assets. Both mediating variables have significantly negative coefficients on CPU, while their coefficients on the firm's TFP are significantly positive, indicating that they both serve as mediators between CPU and

TFP. In an uncertain environment with high climate risks, firms face the challenge of low-carbon transformation, and it is expected that they would reduce some acquisition investments as a precautionary measure (Bretschger and Soretz, 2022; Kong et al., 2022). The disruption in cash flow and capital caused by CPU also forces firms to cut back on some capital expenditures (Ren et al., 2022a). Lower capital intensity leads to lower TFP for the firm.

*Insert Table 10*

#### **4.5. Robustness tests**

To verify the reliability of our empirical findings, we conduct robustness tests using three different methods. Firstly, we adopt an alternative approach for estimating TFP. We replace the LP method with the approach proposed by İmrohoroglu and Tüzel (2014), referred to as TFPIT in this study. The details of this method have been elaborated in section 3.2.1. As shown in Table 11, the coefficient corresponding to CPU remains significantly negative at the 1% level, suggesting that the selection of TFP estimation method does not influence the results. Furthermore, the other results largely remain consistent with the baseline regression results, reinforcing the robustness of above findings.

*Insert Table 11*

Secondly, to avoid the potential influence of specific events on the results, we conduct sub-sample testing by excluding the samples from the years 2000-2001 and 2018-2019. These years are excluded due to the significant impact of events such as the September 11 attacks and the trade disputes between China and the U.S. on the global economy. By shortening the time window, we aim to assess the stability of the

relationship between CPU and firm TFP. The new regression results are presented in Table 12. Notably, the coefficient of CPU remains significantly negative at the 1% level, indicating the consistent finding.

***Insert Table 12***

Thirdly, we perform additional tests to examine whether the inclusion of different or additional variables makes a difference to the results. We implement three treatments: (1) substituting total sales for total assets as a measure of firm size; (2) using return on assets (ROA) instead of ROE to gauge the firm's profitability; and (3) introducing R&D intensity and payout ratio as new control variables. The results are presented in Table 13.

Significantly, the direction and significance of the impact of CPU on firm-level TFP remain consistent even after changing or adding control variables. Additionally, the other results exhibit a high degree of consistency with the baseline findings. Among the newly introduced variables, R&D intensity demonstrates a significantly negative impact on TFP. This observation may be attributed to the fact that substantial investments in research and development often require a considerable amount of time to yield tangible results, resulting in a large capital expenditure in the current period. Besides, the effect of the payout ratio on firm TFP is not statistically significant.

***Insert Table 13***

In conclusion, the above robustness tests suggest that our results are not influenced by variations in TFP measurement methods, sample composition, or missing variables. These tests provide strong evidence for the robustness and reliability of our empirical findings.

### 5. Further Analysis: Local Projection Instrumental Variable approach

For a more dynamic exploration of the relationship between CPU and TFP, we employ the Local Projection Instrumental Variable (LP-IV) method proposed by Jordà (2005) for further investigation. This approach offers notable advantages, enhancing the academic rigor of our study. Firstly, the LP-IV method does not require specific assumptions about the relationships among economic variables, enabling robust estimation using micro-level data. Secondly, compared to the VAR method, LP-IV allows for greater flexibility by incorporating control variables and fixed effects to account for firm heterogeneity. Thirdly, unlike traditional fixed-effects panel models, the LP-IV method enables the estimation of impulse response functions to analyze the dynamic impact of CPU on TFP. This methodology has also been applied in the research conducted by Cloyne et al. (2023).

The specific configuration of the local projection method used here is as follows:

$$\Delta TFP_{i,t,h} = \beta_h \Delta CPU_t + \gamma_h X_{i,t} + \theta_h L^p(w_{i,t}) + \alpha_{i,h} + \delta_{t,h} + e_{i,t+h} \quad \#(4)$$

where

$$\Delta TFP_{i,t,h} = TFP_{i,t+h} - TFP_{i,t} \quad \#(5)$$

$TFP_{i,t}$  means the level of TFP for firm  $i$  in the  $t$ -th year following the occurrence of the shock. To maintain consistency with the above, we adopt the variation in the natural logarithm of CO<sub>2</sub> emissions ( $\Delta \ln CO_{2,t}$ ) as the instrumental variable for  $\Delta CPU_t$  to identify the impact of climate policy uncertainty, utilizing 2SLS to estimate the coefficient  $\beta_h$ .  $\beta_h$  represents the strength of the firm-level TFP's response to the CPU shock in phase  $h$ .  $X_{i,t}$  represents a set of contemporaneous control variables, and  $w_{i,t}$  represents a set of lagged control variables. The lag operator is denoted as  $L^p$ . Given

the annual frequency and relatively short span of the sample data, we set  $p=1$ , indicating the use of control variables lagged by one period.  $\alpha$  captures firm fixed effects,  $\delta$  captures firm fixed effects, and  $e$  represents the residual term in the model.

Based on this, the impulse response values of firm-level TFP are presented in Table 14. To illustrate the changing trends in the impact of climate policy shocks more intuitively, Figure 4 presents the results of the local projection regressions in the form of impulse response graphs. Obviously, the effect of CPU on TFP varies with time, which proves the necessity of using LP-IV method to study dynamic causality. In the initial phase following the shock, an increase in CPU significantly impedes TFP at the firm level, with the most pronounced adverse effect manifesting in the third year. Subsequently, the impact of CPU on TFP turns positive. This suggests that climate policy uncertainty presents not only risks but also opportunities and prospects for development in corporate productivity.

These findings provide insights for companies to enhance policy risk and climate risk management. In response to the initial adverse effects and subsequent potential positive impacts of climate policy uncertainty, firms should adopt proactive and adaptive strategies to strengthen internal risk management and sustainability innovation. This includes investing in clean technologies, optimizing energy management, and intensifying the monitoring of climate change trends to ensure timely understanding and influence on policy developments. Concurrently, firms ought to construct flexible business models that can swiftly respond to policy shifts, seizing new opportunities that arise from climate policy responses, thereby maintaining competitiveness in an evolving policy landscape.

***Insert Table 14***

*Insert Figure 4***6. Conclusions**

Under the global carbon neutrality process, the climate game between major powers has become a crucial issue in international relations, and the uncertainty of climate policies profoundly affects socioeconomic decision-making. This study delves into the influence of CPU on firm-level TFP employing data from publicly listed companies in North America from 2000 to 2019. The empirical analysis reveals that the rise in CPU significantly reduces firms' TFP. The influence of CPU on TFP varies across different types of firms. The negative impact of CPU is more pronounced for firms in the secondary sector, with higher credit ratings, smaller Tobin's Q values, and higher profitability. The underlying mechanisms primarily involve increased operating costs, reduced inventory turnover, and constrained investments. By employing the LP-IV method, we further explore the relationship from a dynamic perspective. The findings indicate that the negative effect of CPU on TFP reaches its peak in the third year following the occurrence of the uncertainty shock. Subsequently, CPU could potentially exert positive influences on TFP.

Enterprises are commonly regarded as the primary agents for energy conservation and emission reduction. The findings of our research contribute a novel perspective for analyzing the interplay between climate policies and market economies. Policymakers should enhance the continuity and predictability of climate policies while paying closer attention to their economic effects and maintaining interaction with the market. It is essential to explore policy combinations that balance environmental improvement and economic development. For companies facing

setbacks due to climate policy change, the government should implement targeted support policies to help them enhance their resilience and competitiveness.

Meanwhile, investors are increasingly concerned about companies' ESG performance. Enterprises need to make efforts to accelerate the pace of transformation and learn how to systematically identify and manage climate risks. Enhancing their ability to withstand climate transition risks is not a helpless response to climate policy restrictions but a proactive approach to seize new market opportunities.

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## Tables

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**Table 14** Regression results based on LP-IV method.

**Table 1**

Variables and their definitions.

| Variable                                    | Abb<br>r.           | Description                                                                                                                                                    |
|---------------------------------------------|---------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>Dependent Variable</b>                   |                     |                                                                                                                                                                |
| Total Factor Productivity                   | TFP                 | The method proposed by Levinsohn and Petrin (2003) is used to measure TFP. In the robustness test, the method of İmrohoroglu and Tüzel (2014) is used instead. |
| <b>Independent Variables</b>                |                     |                                                                                                                                                                |
| Climate Policy Uncertainty                  | CP<br>U             | Index constructed by Gavrilidis, K. (2021). Here we take its natural logarithm                                                                                 |
| <b>Control Variables</b>                    |                     |                                                                                                                                                                |
| Firm Size                                   | Size                | Natural logarithm of firm's total assets                                                                                                                       |
| Leverage                                    | Lev                 | Total liabilities/(total assets*100)                                                                                                                           |
| Return on Equity                            | RO<br>E             | Net profit/(average shareholders' equity*100)                                                                                                                  |
| Liquidity Ratio                             | Liq<br>uidit<br>y   | Current assets/ current liabilities                                                                                                                            |
| Tangibility of Assets                       | Tan<br>gibil<br>ity | Sum of total properties, plants and equipment/total assets                                                                                                     |
| Earning Per Share                           | EPS                 | (Net income - dividends on preferred shares)/the number of outstanding shares                                                                                  |
| Cashflow                                    | CF                  | (Income before extraordinary items + amortization & depreciation) / total assets                                                                               |
| Return on Asset                             | RO<br>A             | Net profit/(total assets*100)                                                                                                                                  |
| R&D Intensity                               | R&<br>D             | Research and Development Expense/ total assets                                                                                                                 |
| Payout Ratio                                | Pay<br>out          | (Dividends (preferred)+Dividends (common)+Purchase of common and preferred Stocks)/Income before extraordinary Items                                           |
| <b>Mediating Variables</b>                  |                     |                                                                                                                                                                |
| Selling, general and administrative expense | SG<br>&A            | Natural logarithm of firm's selling, general and administrative expense                                                                                        |

|                          |            |                                               |
|--------------------------|------------|-----------------------------------------------|
| Finished goods inventory | Invf<br>g  | Total value of finished goods /1000           |
| Acquisitions             | Aqc        | Natural logarithm of firm's acquisition value |
| Capital Intensity        | Cap<br>iin | Capital expenditures/ total assets            |

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Note: Financial data about the firm (such as total assets, total liabilities, net income, dividends, etc.) are derived from its financial statements. Units are in millions of dollars.

**Table 2**

Summary descriptive statistics of final sample.

| Variable    | N     | Mean    | Std.dev. | Min     | P50     | Max     |
|-------------|-------|---------|----------|---------|---------|---------|
| TFP         | 45441 | -0.2081 | 0.5903   | -5.9834 | -0.2192 | 3.321   |
| CPU         | 45441 | 4.2644  | 0.621    | 3.2232  | 4.4359  | 5.2979  |
| Size        | 45441 | 6.746   | 1.951    | 2.8167  | 6.6559  | 11.7458 |
| Lev         | 45291 | 0.0074  | 0.0231   | -0.0943 | 0.004   | 0.1364  |
| ROE         | 45423 | -0.0005 | 0.0038   | -0.0275 | 0.0004  | 0.0032  |
| Liquidity   | 44498 | 2.3547  | 1.6891   | 0.3934  | 1.8808  | 11.0643 |
| Tangibility | 45441 | 0.2655  | 0.225    | 0.0102  | 0.1925  | 0.8802  |
| EPS         | 45425 | 0.9498  | 2.3716   | -7.1226 | 0.6595  | 10.0356 |
| CF          | 45354 | 0.0709  | 0.0995   | -0.3897 | 0.0797  | 0.3175  |
| SG&A        | 43485 | 5.0135  | 1.747    | -1.4397 | 4.909   | 11.5868 |
| Invfg       | 32091 | 0.217   | 0.874    | -0.0056 | 0.0135  | 19.868  |
| Aqc         | 19541 | 3.2954  | 2.3652   | -6.9078 | 3.3899  | 11.1066 |
| Capiin      | 45441 | 0.0515  | 0.0556   | 0       | 0.0339  | 0.8727  |

Note: The table shows summary statistics for main variables used in the study. Table 1 provides the definitions of the variables.

**Table 3**

Correlation coefficients between the main variables.

| Variable        | TFP               | CPU               | Size              | Lev               | ROE               | Liquidit<br>y     | Tangibilit<br>y | EPS          | CF        |
|-----------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-----------------|--------------|-----------|
| TFP             | 1.000             |                   |                   |                   |                   |                   |                 |              |           |
| CPU             | 0.008*            | 1.000             |                   |                   |                   |                   |                 |              |           |
| Size            | 0.148**<br>*      | 0.202**<br>*      | 1.000             |                   |                   |                   |                 |              |           |
| Lev             | -<br>0.025**<br>* | 0.013**           | 0.107**<br>*      | 1.000             |                   |                   |                 |              |           |
| ROE             | 0.264**<br>*      | 0.006             | 0.108**<br>*      | -<br>0.028**<br>* | 1.000             |                   |                 |              |           |
| Liquidity       | 0.065**<br>*      | -<br>0.034**<br>* | -<br>0.245**<br>* | -<br>0.114**<br>* | 0.105**<br>*      | 1.000             |                 |              |           |
| Tangibilit<br>y | -<br>0.271**<br>* | 0.003             | 0.180**<br>*      | 0.083**<br>*      | -<br>0.038**<br>* | -<br>0.250**<br>* | 1.000           |              |           |
| EPS             | 0.337**<br>*      | 0.078**<br>*      | 0.338**<br>*      | -<br>0.019**<br>* | 0.521**<br>*      | -<br>0.010**<br>* | 0.013***        | 1.000        |           |
| CF              | 0.468**<br>*      | -<br>0.017**<br>* | 0.170**<br>*      | -<br>0.041**<br>* | 0.591**<br>*      | 0.056**<br>*      | 0.136***        | 0.590**<br>* | 1.00<br>0 |

Note: The table shows the correlation coefficients of the main variables. Table 1 provides the definitions of the variables. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

**Table 4**

Baseline results.

| Variable                  | Dependent variable: TFP <sub>it</sub> |                              |                              |                              |                              |                              |                              |                                  |
|---------------------------|---------------------------------------|------------------------------|------------------------------|------------------------------|------------------------------|------------------------------|------------------------------|----------------------------------|
|                           | (1)                                   | (2)                          | (3)                          | (4)                          | (5)                          | (6)                          | (7)                          | (8)                              |
| CPU <sub>t</sub>          | -<br>0.0914***<br>(-11.8169)          | -<br>0.1795***<br>(-18.7004) | -<br>0.1794***<br>(-18.6913) | -<br>0.1544***<br>(-17.1292) | -<br>0.1488***<br>(-16.3189) | -<br>0.1509***<br>(-16.8740) | -<br>0.1667***<br>(-19.0639) | -<br>0.1403***<br>(-17.6655)     |
| Size <sub>it</sub>        |                                       | 0.1509***<br>(16.8209)       | 0.1523***<br>(16.8881)       | 0.1401***<br>(16.3765)       | 0.1377***<br>(15.9767)       | 0.1306***<br>(15.4917)       | 0.1173***<br>(14.2797)       | 0.1398***<br>(18.4219)           |
| Lev <sub>it</sub>         |                                       |                              | -<br>0.5017***<br>(-4.0215)  | -<br>0.5441***<br>(-4.4960)  | -<br>0.5277***<br>(-4.2769)  | -<br>0.5374***<br>(-4.4188)  | -<br>0.4335***<br>(-3.5790)  | -0.2358**<br>(-2.1377)           |
| ROE <sub>it</sub>         |                                       |                              |                              | 31.4280**<br>*<br>(27.5412)  | 30.5487**<br>*<br>(26.8197)  | 29.2635**<br>*<br>(25.8795)  | 14.0785**<br>*<br>(11.8261)  | -<br>10.0935**<br>*<br>(-7.9778) |
| Liquidity <sub>it</sub>   |                                       |                              |                              |                              | 0.0243***<br>(6.7117)        | 0.0133***<br>(3.6522)        | 0.0121***<br>(3.4455)        | 0.0021<br>(0.6896)               |
| Tangibility <sub>it</sub> |                                       |                              |                              |                              |                              | -<br>0.8839***<br>(-16.7300) | -<br>0.8039***<br>(-15.7059) | -<br>0.8773***<br>(-19.2612)     |
| EPS <sub>it</sub>         |                                       |                              |                              |                              |                              |                              | 0.0528***<br>(24.5466)       | 0.0092***<br>(4.3212)            |
| CF <sub>it</sub>          |                                       |                              |                              |                              |                              |                              |                              | 2.5692***<br>(41.2580)           |
| IE                        | Yes                                   | Yes                          | Yes                          | Yes                          | Yes                          | Yes                          | Yes                          | Yes                              |
| YE                        | Yes                                   | Yes                          | Yes                          | Yes                          | Yes                          | Yes                          | Yes                          | Yes                              |
| Constant                  | 0.2254***<br>(6.8310)                 | -<br>0.4305***<br>(-8.8695)  | -<br>0.4360***<br>(-8.9538)  | -<br>0.4435***<br>(-9.4620)  | -<br>0.5107***<br>(-10.7589) | -<br>0.1727***<br>(-3.3269)  | -0.0988*<br>(-1.9447)        | -<br>0.4756***<br>(-10.2574)     |
| Observations              | 45,441                                | 45,441                       | 45,291                       | 45,273                       | 44,341                       | 44,341                       | 44,341                       | 44,255                           |
| R-squared                 | 0.0267                                | 0.0568                       | 0.0575                       | 0.1335                       | 0.1369                       | 0.1564                       | 0.2057                       | 0.3536                           |

Note: The table shows the baseline regression results with CPU as the independent variable and firm-level TFP as the dependent variable. Table 1 provides the definitions of the variables. The t-statistics for the coefficients are presented in parentheses. \*\*, and \*\*\* denote significance at the 5%, and 1% levels, respectively.

**Table 5**

Endogenous test based on 2SLS estimation.

| Variable                            | 2SLS Estimation        |                          |
|-------------------------------------|------------------------|--------------------------|
|                                     | CPU <sub>t</sub>       | TFP <sub>it</sub>        |
| lnCO <sub>2,t</sub>                 | -4.5367***<br>(0.0524) |                          |
| CPU <sub>t</sub>                    |                        | -0.2634***<br>(-19.4608) |
| Size <sub>it</sub>                  | 0.1706***<br>(0.0073)  | 0.1746***<br>(19.8598)   |
| Lev <sub>it</sub>                   | -0.1503<br>(0.1361)    | -0.2338**<br>(-1.9717)   |
| ROE <sub>it</sub>                   | -6.9455***<br>(1.0928) | -12.1464***<br>(-9.0060) |
| Liquidity <sub>it</sub>             | -0.1091***<br>(0.0032) | 0.0000<br>(0.0033)       |
| Tangibility <sub>it</sub>           | -0.2223***<br>(0.0507) | -0.8625***<br>(-18.4470) |
| EPS <sub>it</sub>                   | 0.0085***<br>(0.0018)  | 0.0110***<br>(5.0220)    |
| CF <sub>it</sub>                    | -0.2306***<br>(0.0496) | 2.5157***<br>(39.0458)   |
| IE                                  | Yes                    | Yes                      |
| Constant                            | 42.1635<br>(0.4466)    | -0.2286***<br>(-4.5215)  |
| Kleibergen-Paap rk LM statistic     | 1009.12                |                          |
| Kleibergen-Paap rk Wald F statistic | 7495.78                |                          |
| Observations                        | 43,392                 | 43,392                   |
| R-squared                           | 0.3087                 | 0.2457                   |

Note: The table shows the results of endogeneity analysis using 2SLS estimation. Table 1 provides the definitions of the variables. The robust standard errors for the coefficients are presented in parentheses. \*\*\* denotes significance at the 1% level.

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**Table 6**

Heterogeneity analysis based on different industrial types.

| Variable           | Dependent variable: $TFP_{it}$ |                          |                          |
|--------------------|--------------------------------|--------------------------|--------------------------|
|                    | Primary Industry               | Secondary Industry       | Tertiary Industry        |
|                    | (1)                            | (2)                      | (3)                      |
| $CPU_t$            | -0.1513*<br>(-1.7281)          | -0.1526***<br>(-15.3078) | -0.1163***<br>(-8.9609)  |
| $Size_{it}$        | 0.2166***<br>(2.9128)          | 0.1529***<br>(15.3350)   | 0.1204***<br>(10.5224)   |
| $Lev_{it}$         | -0.9971<br>(-0.6842)           | -0.4089**<br>(-2.1480)   | -0.0813<br>(-0.6390)     |
| $ROE_{it}$         | -2.4279<br>(-0.2636)           | -9.8126***<br>(-5.1993)  | -7.1647***<br>(-4.3158)  |
| $Liquidity_{it}$   | -0.0214<br>(-0.6806)           | 0.0008<br>(0.2253)       | 0.0036<br>(0.6562)       |
| $Tangibility_{it}$ | -0.8270***<br>(-2.7350)        | -0.9569***<br>(-14.2677) | -0.7432***<br>(-12.4109) |
| $EPS_{it}$         | -0.0164<br>(-0.9430)           | 0.0127***<br>(4.4109)    | 0.0001<br>(0.0388)       |
| $CF_{it}$          | 2.7924***<br>(3.3236)          | 2.8949***<br>(33.6148)   | 2.1230***<br>(24.3723)   |
| IE                 | Yes                            | Yes                      | Yes                      |
| YE                 | Yes                            | Yes                      | Yes                      |
| Constant           | -1.0022**<br>(-2.1229)         | -0.5582***<br>(-8.5083)  | -0.3903***<br>(-5.9692)  |
| Observations       | 416                            | 24,947                   | 18,892                   |
| R-squared          | 0.3399                         | 0.3986                   | 0.2991                   |
| Chow Test          |                                | 108.43                   |                          |
| P-value            |                                | 0.0000                   |                          |
| Number of cp       | 67                             | 3,067                    | 2,708                    |

Note: The table shows the results of heterogeneity analysis of CPU's effect on firm-level TFP considering industry type. Table 1 provides the definitions of the variables. The t-statistics for the coefficients are presented in parentheses. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively. The P-value for testing the differences in coefficients between groups is calculated based on the estimates from the Chow test.

**Table 7**

Heterogeneity analysis based on different S&amp;P ratings.

| Variable                  | Dependent variable: TFP <sub>it</sub> |                         |
|---------------------------|---------------------------------------|-------------------------|
|                           | Highly-rated                          | Low-rated               |
|                           | (1)                                   | (2)                     |
| CPU <sub>t</sub>          | -0.1418***<br>(-15.5657)              | -0.1286***<br>(-7.5364) |
| Size <sub>it</sub>        | 0.1371***<br>(14.8960)                | 0.1447***<br>(10.5850)  |
| Lev <sub>it</sub>         | -0.0794<br>(-0.5929)                  | -0.4778**<br>(-2.5530)  |
| ROE <sub>it</sub>         | -10.7027***<br>(-5.6846)              | -9.1726***<br>(-5.0001) |
| Liquidity <sub>it</sub>   | 0.0004<br>(0.1090)                    | 0.0057<br>(0.9079)      |
| Tangibility <sub>it</sub> | -0.9011***<br>(-17.1078)              | -0.8349***<br>(-9.6893) |
| EPS <sub>it</sub>         | 0.0077***<br>(3.3750)                 | 0.0110**<br>(2.2463)    |
| CF <sub>it</sub>          | 2.6380***<br>(32.4276)                | 2.4718***<br>(25.5034)  |
| IE                        | Yes                                   | Yes                     |
| YE                        | Yes                                   | Yes                     |
| Constant                  | -0.4660***<br>(-8.5063)               | -0.5099***<br>(-5.4915) |
| Observations              | 32,128                                | 12,127                  |
| R-squared                 | 0.3603                                | 0.3476                  |
| Chow Test                 | 11.69                                 |                         |
| P-value                   | 0.0000                                |                         |
| Number of cp              | 4,344                                 | 1,498                   |

Note: The table shows the results of heterogeneity analysis of CPU's effect on firm-level TFP considering credit ratings. Firms rated A and B are highly-rated group, and

the results are listed in column (1). Firms rated C and D are low-rated group, and the results are listed in column (2). Table 1 provides the definitions of the variables. The t-statistics for the coefficients are presented in parentheses. \*\*, and \*\*\* denote significance at the 5%, and 1% levels, respectively. The P-value for testing the differences in coefficients between groups is calculated based on the estimates from the Chow test.

**Table 8**

Heterogeneity analysis based on Tobin's Q value.

| Variable                  | Dependent variable: TFP <sub>it</sub> |                         |
|---------------------------|---------------------------------------|-------------------------|
|                           | Tobin's Q > 1                         | Tobin's Q ≤ 1           |
|                           | (1)                                   | (2)                     |
| CPU <sub>t</sub>          | -0.1479***<br>(-16.5374)              | -0.1630***<br>(-8.0450) |
| Size <sub>it</sub>        | 0.1427***<br>(17.3703)                | 0.1506***<br>(7.1700)   |
| Lev <sub>it</sub>         | -0.1960*<br>(-1.7070)                 | 2.0483***<br>(2.7356)   |
| ROE <sub>it</sub>         | -15.7646***<br>(-8.8616)              | 8.1316***<br>(3.9258)   |
| Liquidity <sub>it</sub>   | 0.0041<br>(1.3163)                    | -0.0028<br>(-0.3317)    |
| Tangibility <sub>it</sub> | -0.8606***<br>(-17.5501)              | -0.5892***<br>(-4.3192) |
| EPS <sub>it</sub>         | 0.0097***<br>(4.1280)                 | 0.0065<br>(1.4066)      |
| CF <sub>it</sub>          | 2.7010***<br>(38.7436)                | 1.4205***<br>(10.1506)  |
| IE                        | Yes                                   | Yes                     |
| YE                        | Yes                                   | Yes                     |
| Constant                  | -0.4716***<br>(-9.3687)               | -0.5158***<br>(-3.8582) |
| Observations              | 37,130                                | 7,125                   |
| R-squared                 | 0.3593                                | 0.3080                  |
| Chow Test                 | 47.77                                 |                         |
| P-value                   | 0.0000                                |                         |
| Number of cp              | 5,353                                 | 2,511                   |

Note: The table shows the results of heterogeneity analysis of CPU's effect on firm-level TFP considering market performance. Column (1) reports the regression results

for the observations with Tobin's  $Q > 1$ , while column (2) reports the results for those with Tobin's  $Q \leq 1$ . Table 1 provides the definitions of the variables. The t-statistics for the coefficients are presented in parentheses. \*, and \*\*\* denote significance at the 10%, and 1% levels, respectively. The P-value for testing the differences in coefficients between groups is calculated based on the estimates from the Chow test.

**Table 9**

Heterogeneity analysis based on profitability.

| Variable                  | Dependent variable: TFP <sub>it</sub> |                          |
|---------------------------|---------------------------------------|--------------------------|
|                           | High Profit                           | Low Profit               |
|                           | (1)                                   | (2)                      |
| CPU <sub>it</sub>         | -0.1812***<br>(-17.1250)              | -0.0928***<br>(-8.9452)  |
| Size <sub>it</sub>        | 0.1461***<br>(15.1544)                | 0.1231***<br>(12.3750)   |
| Lev <sub>it</sub>         | 0.2135*<br>(1.6479)                   | -0.2726**<br>(-2.0690)   |
| ROE <sub>it</sub>         | -125.3549***<br>(-13.5266)            | -1.1891<br>(-0.9452)     |
| Liquidity <sub>it</sub>   | 0.0031<br>(1.0566)                    | -0.0136***<br>(-2.6023)  |
| Tangibility <sub>it</sub> | -0.7837***<br>(-13.1118)              | -0.8243***<br>(-13.8594) |
| EPS <sub>it</sub>         | 0.0188***<br>(6.5463)                 | -0.0017<br>(-0.6078)     |
| CF <sub>it</sub>          | 2.6719***<br>(23.6253)                | 2.0214***<br>(26.0815)   |
| IE                        | Yes                                   | Yes                      |
| YE                        | Yes                                   | Yes                      |
| Constant                  | -0.3040***<br>(-4.6574)               | -0.5567***<br>(-8.8835)  |
| Observations              | 20,694                                | 23,561                   |
| R-squared                 | 0.2962                                | 0.2403                   |
| Chow Test                 | 457.11                                |                          |
| P-value                   | 0.0000                                |                          |
| Number of cp              | 3,881                                 | 4,983                    |

Note: The table shows the results of heterogeneity analysis of CPU's effect on firm-level TFP considering profitability. Those whose net profit margin is higher than the

median are high profit groups, otherwise they are low profit groups. Column (1) reports the regression results for high profit firms, while column (2) reports the results for those low profit firms. Table 1 provides the definitions of the variables. The t-statistics for the coefficients are presented in parentheses. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively. The P-value for testing the differences in coefficients between groups is calculated based on the estimates from the Chow test.

**Table 10**

Channel analysis.

[illegible]

|              |                          |                       |                         |                         |                         |                         |                         |                        |                          |
|--------------|--------------------------|-----------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|------------------------|--------------------------|
| IE           | Yes                      | Yes                   | Yes                     | Yes                     | Yes                     | Yes                     | Yes                     | Yes                    | Yes                      |
| YE           | Yes                      | Yes                   | Yes                     | Yes                     | Yes                     | Yes                     | Yes                     | Yes                    | Yes                      |
| Constant     | -0.4756***<br>(-10.2574) | 0.1556***<br>(2.7282) | -0.4416***<br>(-9.4801) | -0.5235***<br>(-6.3007) | -0.4911***<br>(-9.0098) | -1.6721***<br>(-5.7224) | -0.2958***<br>(-4.7738) | 0.0801***<br>(17.3197) | -0.5604***<br>(-11.9390) |
| Observations | 44,255                   | 42,479                | 42,479                  | 31,438                  | 31,438                  | 19,069                  | 19,069                  | 44,255                 | 44,255                   |
| R-squared    | 0.3536                   | 0.7393                | 0.3614                  | 0.0613                  | 0.3628                  | 0.1311                  | 0.3203                  | 0.1183                 | 0.3616                   |

Note: The table shows the results of mediating effects of four mediating variables on the CPU's effect on firm-level TFP. Column (1) presents the baseline regression results. Columns(2,3) report the results with SG&A; Columns(4,5) are for finished goods inventory(Invfg);Columns (6,7) are for acquisitions(Aqc);and the last Columns (8,9) are for capital intensity(Capiin). Table 1 provides the definitions of the variables. The t-statistics for the coefficients are presented in parentheses. \*\*\* denotes significance at the 1% level.

**Table 11**

Robustness test by changing the measurement method of TFP.

| Variable                  | Dependent variable: TFPIT <sub>it</sub> |
|---------------------------|-----------------------------------------|
| CPU <sub>t</sub>          | -0.1393***<br>(-16.9625)                |
| Size <sub>it</sub>        | 0.1792***<br>(23.4588)                  |
| Lev <sub>it</sub>         | -0.1834<br>(-1.5903)                    |
| ROE <sub>it</sub>         | -13.6914***<br>(-10.4508)               |
| Liquidity <sub>it</sub>   | 0.0092***<br>(3.3198)                   |
| Tangibility <sub>it</sub> | -0.4302***<br>(-8.8006)                 |
| EPS <sub>it</sub>         | 0.0001<br>(0.0530)                      |
| CF <sub>it</sub>          | 2.4255***<br>(38.5604)                  |
| IE                        | Yes                                     |
| YE                        | Yes                                     |
| Constant                  | -0.9864***<br>(-19.8504)                |
| Observations              | 39412                                   |
| R-squared                 | 0.3071                                  |

Note: The table shows the results of robustness test by changing the TFP calculation method. Table 1 provides the definitions of the variables. The t-statistics for the coefficients are presented in parentheses. \*\*\* denotes significance at the 1% level.

**Table 12**

Robustness test by shortening the sample period.

| Variable           | Dependent variable: $TFP_{it}$ |
|--------------------|--------------------------------|
|                    | From 2002 to 2017              |
| $CPU_t$            | -0.1297***<br>(-15.0140)       |
| $Size_{it}$        | 0.1716***<br>(21.2383)         |
| $Lev_{it}$         | -0.2687**<br>(-2.3440)         |
| $ROE_{it}$         | -12.1260***<br>(-9.2157)       |
| $Liquidity_{it}$   | 0.0103***<br>(3.3388)          |
| $Tangibility_{it}$ | -0.3911***<br>(-7.6916)        |
| $EPS_{it}$         | 0.0016<br>(0.7203)             |
| $CF_{it}$          | 2.2867***<br>(35.1303)         |
| IE                 | Yes                            |
| YE                 | Yes                            |
| Constant           | -0.9819***<br>(-18.7922)       |
| Observations       | 35,258                         |
| R-squared          | 0.2951                         |

Note: The table shows the results of robustness test by shortening the sample period to 2002-2017. Table 1 provides the definitions of the variables. The t-statistics for the coefficients are presented in parentheses. \*\*\* denotes significance at the 1% level.

**Table 13**

Robustness test by replacing or adding control variables.

| Variable                  | Dependent variable: TFP <sub>it</sub> |                          |                           |
|---------------------------|---------------------------------------|--------------------------|---------------------------|
|                           | Replace Size                          | Replace ROE              | Add new control variables |
|                           | (1)                                   | (2)                      | (3)                       |
| CPU <sub>t</sub>          | -0.1674***<br>(-19.3884)              | -0.1358***<br>(-17.2705) | -0.1287***<br>(-12.6887)  |
| Sale <sub>it</sub>        | 0.2190***<br>(21.5487)                |                          |                           |
| Size <sub>it</sub>        |                                       | 0.1383***<br>(18.2806)   | -0.1271<br>(-0.8465)      |
| Lev <sub>it</sub>         | -0.1831*<br>(-1.7190)                 | -0.2727**<br>(-2.4797)   | -12.5086***<br>(-6.5385)  |
| ROE <sub>it</sub>         | -7.8233***<br>(-6.5344)               |                          |                           |
| ROA <sub>it</sub>         | 0.0130***<br>(4.3630)                 | -10.8696**<br>(-2.3624)  |                           |
| Liquidity <sub>it</sub>   | -0.8863***<br>(-18.5596)              | 0.0018<br>(0.5792)       | 0.0021<br>(0.5839)        |
| Tangibility <sub>it</sub> | 0.0068***<br>(3.2829)                 | -0.8641***<br>(-18.9977) | -1.0134***<br>(-16.7399)  |
| EPS <sub>it</sub>         | 2.4138***<br>(40.2665)                | 0.0058***<br>(2.7562)    | -0.0010<br>(-0.3766)      |
| CF <sub>it</sub>          | -0.1831*<br>(-1.7190)                 | 2.4889***<br>(32.9974)   | 2.7417***<br>(34.2327)    |
| R&D <sub>it</sub>         |                                       |                          | -0.7366***<br>(-3.8354)   |
| Payout <sub>it</sub>      |                                       |                          | 0.0000<br>(0.0037)        |
| Constant                  | -0.8748***<br>(-15.7753)              | -0.4708***<br>(-10.1271) | -0.4297***<br>(-6.8398)   |

|              |        |        |        |
|--------------|--------|--------|--------|
| Observations | 44,255 | 44,257 | 26,277 |
| R-squared    | 0.3758 | 0.3500 | 0.3799 |

Note: The table shows the results of robustness test by replacing or adding control variables. Table 1 provides the definitions of the variables. The t-statistics for the coefficients are presented in parentheses. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

**Table 14** Regression results based on LP-IV method.

|                   | h=1                   | h=2                    | h=3                    | h=4                   | h=5                   |
|-------------------|-----------------------|------------------------|------------------------|-----------------------|-----------------------|
|                   | (1)                   | (2)                    | (3)                    | (4)                   | (5)                   |
| $\beta_h$         | 0.0232***<br>(0.0064) | -0.0732***<br>(0.0091) | -0.0894***<br>(0.0147) | 0.1610***<br>(0.0259) | 0.1410***<br>(0.0269) |
| Control variables | Yes                   | Yes                    | Yes                    | Yes                   | Yes                   |
| YE                | Yes                   | Yes                    | Yes                    | Yes                   | Yes                   |
| IE                | Yes                   | Yes                    | Yes                    | Yes                   | Yes                   |
| Observations      | 37132                 | 31592                  | 27367                  | 23890                 | 20866                 |

Note: The table shows regression results for estimating climate policy uncertainty shocks using the LP-IV approach. Standard errors clustered to the firm level are in parentheses. \*\*\* denotes significance at the 1% level.

## Figures

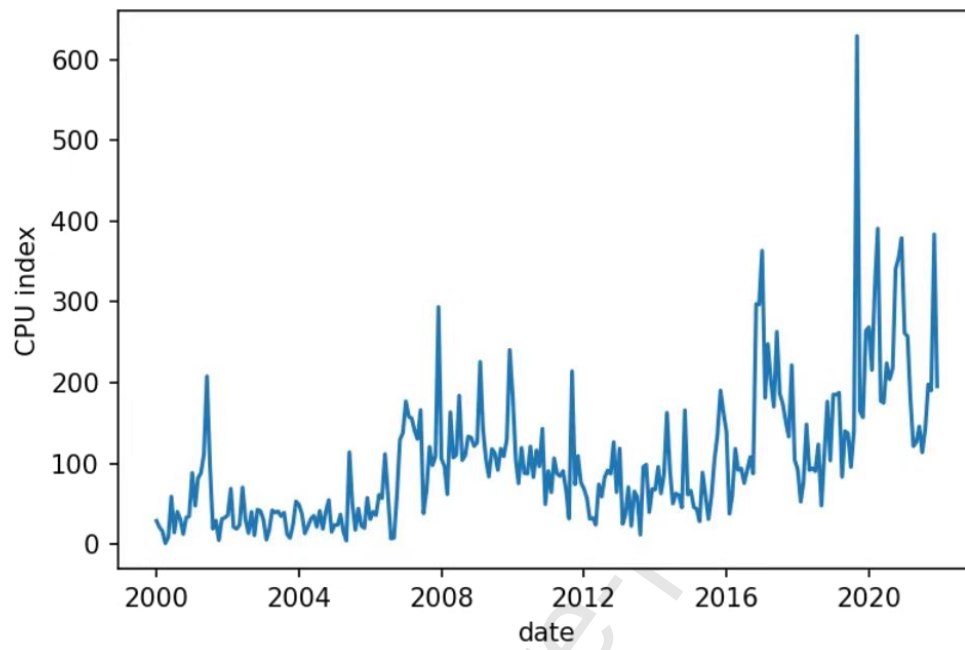
**Fig. 1.** Monthly data of Climate Policy Uncertainty Index.

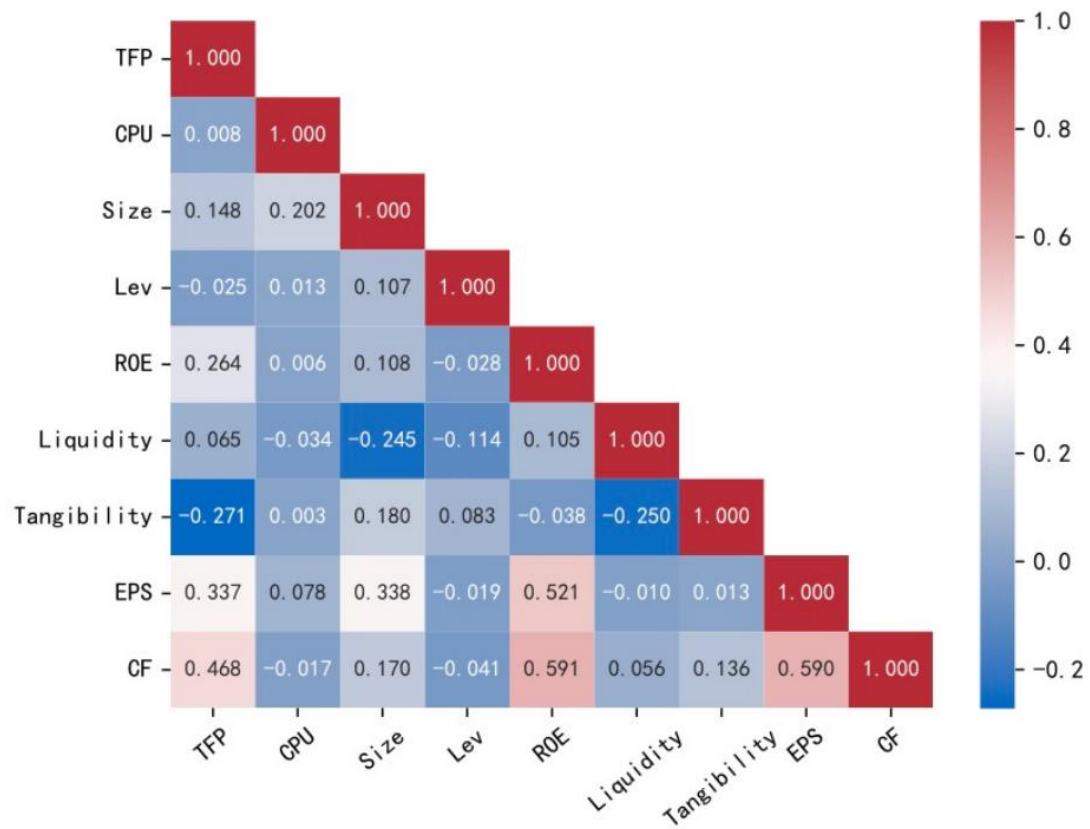
**Fig. 2.** Heatmap of correlation coefficients between main variables.

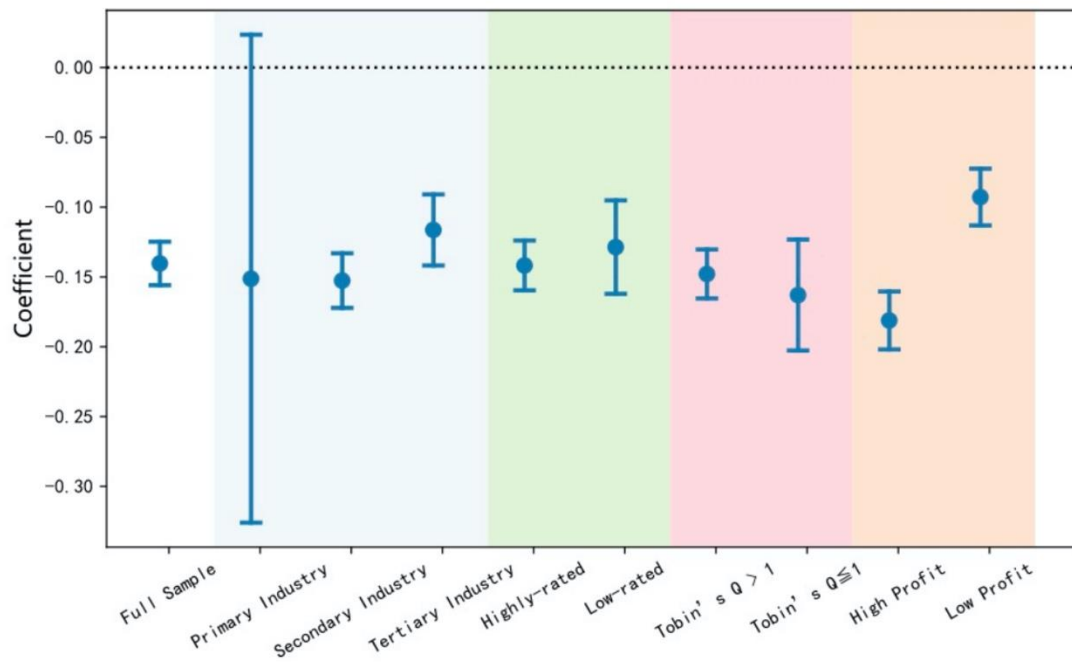
**Fig. 3.** Heterogeneity analysis results.

**Fig. 4.** Impulse response of firm-level TFP to CO<sub>2</sub> emissions.

**Fig. 1.** Monthly data of Climate Policy Uncertainty Index.

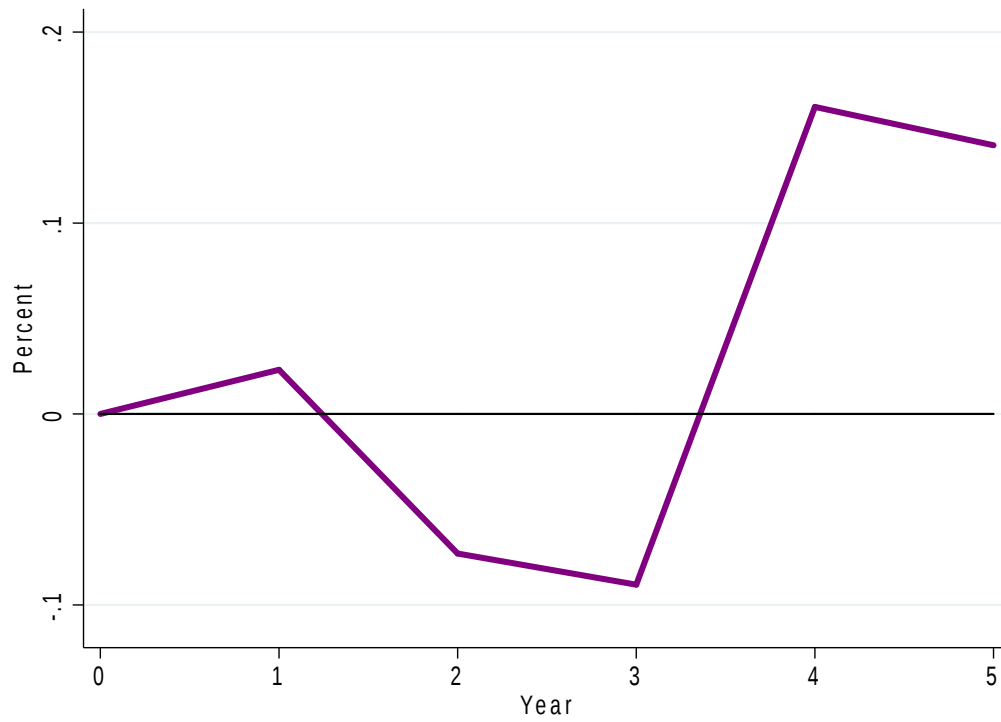


**Fig. 2.** Heatmap of correlation coefficients between main variables.

**Fig. 3.** Heterogeneity analysis results.

Note: The blue dots represent the coefficient values and the lines represent the confidence intervals at the 95% confidence level for the coefficients.

**Fig. 4.** Impulse response of firm-level TFP to CO<sub>2</sub> emissions.



Note: The solid purple line represents the result of the LP-IV method. The shaded part is the 90% confidence band.

## Highlights

- We explore the impact of CPU on TFP in 5,954 North American firms.
- Our findings show that an increase in CPU significantly decreases firms' TFP.
- The heterogeneity of sub-indicators and impact mechanisms between CPU and TFP are also examined.
- The event of Trump's announcement of withdrawal from the Paris Agreement in 2017 on TFP is studied as a robustness check.