Climate Policy Uncertainty and Firm Pollutant Emissions

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Abstract

This paper studies the effect of climate policy uncertainty on firm environmental performance. The evidence suggests that firms reduce toxic emissions and close toxic facilities during the heightened climate policy uncertainty periods. Contrary to the prediction of the real options theory that uncertainty increases the option value of waiting and therefore defers the investment, I find that firms respond to climate policy uncertainty by adopting abatement technology to reduce pollution. Further analyses suggest that when climate policy uncertainty increases, polluting firms are more likely to incur the U.S. Environmental Protection Agency (EPA) penalties, violations, and enforcement, have higher compliance costs, and experience larger declines in institutional holdings. The reduction of toxic emissions is not driven by the declines in production activities. Exploiting the number of Congressional voting on the topics related to climate change annually as an instrument for climate policy uncertainty, I argue that the effects of climate policy uncertainty on the reduction of toxic emissions and the closures of toxic facilities are likely to be causal.

Keywords: climate policy uncertainty, toxic emissions, regulatory costs, abatement activities, institutional holdings.

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I. Introduction

In the current political climate, climate change and the related policy have received increased attention from academics and the media due to the raising public awareness on climate change. According to the United Nation, industrial pollution have contributed significantly to climate change, which threatens people with food and water scarcity, increased flooding, extreme heat, more disease, and economic loss. Government's environmental policy plays an important role in preventing industrial pollution (Shapiro and Walker, 2018). Despite this fact, there could be substantial uncertainty on the implementation of the regulation and legislation. For example, the withdraw of the U.S. from the Paris Agreement in 2017 has created uncertainty on the future path of the climate policy in the U.S. How does uncertainty in climate policy change firms' decisions? This paper, therefore, investigates the impact of climate policy related uncertainty on firms' polluting behaviors.

A priori, neither the direction nor the magnitude of the effects of climate policy uncertainty on firm pollution is clear. On the one hand, the classical real options theory suggests that uncertainty could increase the option value of waiting and hold up the investment decisions (Dixit and Pindyck, 1994; Durnev, 2013; Gulen and Ion, 2016; Julio and Yook, 2012; Jens, 2017; Basaglia, Carattini, Dechezlepretre and Kruse, 2020). Climate policy uncertainty, probably like other types of market uncertainty, hinders firms' investment in the clean technology. Consequently, the deterred investment in the abatement technology would lead to firm pollution.

On the other hand, climate policy uncertainty poses regulatory risks on pollutant firms. Seltzer, Starks and Zhu (2021) explore the environmental regulatory uncertainty attached to the withdrawn of U.S. from the Paris Agreement in 2017. They find that climate regulatory risks lead to the decreases in bond ratings and the increase in yield spread. If firms anticipate that the future environmental regulatory costs would increase, it may motivate them to adopt the abatement technology to minimize the expected cost of emission in the future. Fried, Novan and Peterman (2021) study the macro effects of climate policy risk and theoretically derive that climate policy risk reduces the aggregate carbon emissions by causing the capital stock to shrink and become relatively clear. Therefore, climate policy uncertainty may lead to the reduction in toxic releases if firms anticipate the future cost of pollution would increase with climate policy uncertainty.

This paper suggests that firms reduce pollutant emissions and close toxic facilities when climate policy uncertainty increases. While the firms do not decrease production, they reduce emissions at the source as a result of the increased abatement activities. The findings contradict the classic real options theory that uncertainty increases the option value of waiting and impedes investment. Further analyses suggest that firms are more likely to get the U.S. Environmental Protection Agency (EPA) penalties, violations, and enforcement, incur higher compliance costs, and experience institutional ownership declines under high climate policy uncertainty. Therefore, I argue that under climate policy uncertainty, the expected regulatory cost over-weights the option value of waiting. As a consequence, climate policy uncertainty leads the adoption of abatement technology and therefore, reduces pollutant emissions.

Starting with a simple dynamic model focusing on the investment of the abatement technology, I highlight the channel through which climate policy uncertainty increases the adoption of the abatement technology. Specifically, climate policy uncertainty lowers the trigger regulatory cost to adopt the abatement technology to improve environmental performance. The model implies that uncertainty about whether and when the U.S. government changes its climate policy introduces risk into the decision to invest capital in the abatement technology.

To empirically test the implication of the model, I need a measure of climate policy uncertainty (CPU). However, the lack of uncertainty measures specifically on climate policy posts a challenge on this study. Using the recently developed index on climate policy uncertainty by Gavriilidis (2021), this paper is able to overcome the challenge. Gavriilidis (2021) measures climate policy uncertainty as follows. He first searches for articles in eight leading U.S.

newspapers[1] containing the keywords on uncertainty, climate, and regulations from 2000 to 2021. For each newspaper, he scales the number of relevant articles per month with the total number of articles during the same month. Next, these eight series are standardized to have a unit standard deviation and then averaged across newspapers by month for the period 2000 to 2021.

Using the CPU index developed by Gavriilidis (2021) and a sample of U.S. public firms reporting toxic release to the EPA between 2000 and 2020, I first examine how climate policy uncertainty influences firm- and plant-level pollution. I find that firms respond to CPU by significantly reducing toxic emissions at the firm- and plant-level and closing toxic facilities. I also find that firms reduce greenhouse gas emissions at the plant- and chemical-level.

Besides the challenge on the lack of climate policy uncertainty measures, this paper also faces another challenge of establishing a causal link between CPU and the reduction of toxic releases. A potential concern is that the effect of climate policy uncertainty on firm pollution may be confounded by other unobserved factors. To address this concern, I exploit the instrumental variable approach. In particular, I use the number of Congressional voting on the topics related to climate change every year as an instrument for CPU. The number of Congressional voting is independent from the macroeconomic conditions. Therefore, it is able to disentangle the influences of climate policy uncertainty from other economic factors on toxic emissions. The empirical evidence suggests that the number of Congressional voting is a valid and strong instrumental variable. The results remain robust to the instrumental variable approach.

I next investigate how firms reduce toxic emissions in response to the increase of CPU. According to the model, CPU leads to the adoption of the abatement technology. Therefore, I investigate the impact of CPU on firms' abatement activities. I focus on source reduction, which is the most favorable practice according to the EPA, since it reduces pollution at the source. The results support the model implication that firms reduce pollution through the

[1] The eight newspapers are: Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today, and the Wall Street Journal.

increased abatement activities when CPU increases.

Next, to provide direct evidence on firms' concerns over environmental regulatory activities during the heightened CPU periods, I first study how CPU affects the EPA regulatory intensities. I find that high polluting firms are more likely to receive EPA penalties, violations, enforcement, and incur higher compliance costs when CPU is high. I also study whether CPU accelerates the capital withdrawn by institutional investors from the highly polluting firms. I find significant reductions of institutional ownership in polluting firms during the high CPU periods. Overall, it suggests that highly polluting firms are more likely to be punished through the intensified regulations and the declines of institutional ownership when CPU is high.

The paper also investigates the heterogeneous effects of CPU on toxic emissions. Studies suggest that financial status affects firms' environmental performance (Xu and Kim (2022); Levine, Lin, Wang and Xie (2019)). Therefore, I investigate the interaction effect of financial distress and CPU. I find that the negative impact of CPU on firm pollution is weakened in the financial constrained firms, probably because those firms have limited ability to fund the abatement technology and are less willing to close toxic plants.

Furthermore, existing studies suggest that people's perception of uncertainty varies, although an aggregate uncertainty is identical. Accordingly, I examine whether CEO characteristics, e.g. age and tenure, affect the influence of CPU on toxic releases. On the one hand, younger CEOs and CEOs with short tenure may have limited experience dealing with climate policy uncertainty. On the other hand, those CEOs are probably more concerned about their reputation in the labor market. Incurring the EPA penalties and violations or experiencing large declines in institutional ownership does not add value to their managerial careers. Examining the interaction effects, I find that the impact of CPU on toxic emissions is strengthened in the firms with relatively younger CEOs and CEOs with short tenure.

Additionally, examining the effects of CPU on other outcomes, I find that high CPU leads to lower stock returns and firm valuations, less analysts following, higher stock volatility, and larger analyst forecast dispersion in polluting firms.

The decreases in toxic release could be driven by the declines in production activities. To alleviate this concern, I use the production ratio variable reported in the TRI database to further examine whether the reduction of toxic emissions is caused by the declined production activities. I do not find that CPU significantly changes production in the polluting firms..

Although the climate policy uncertainty measure focuses on the climate policies and regulations, there are still concerns that the results could instead be driven by a general uncertainty which may be captured by the CPU index. To ease this concern, I include non-climate policy uncertainty to the baseline regressions. Specifically, I include economic policy uncertainty (EPU) developed by Baker, Bloom and Davis (2016). I find that EPU does not significantly affect firms' toxic emissions and the closures of toxic facilities. The effects of CPU remain negative and significant on toxic emissions and closures of polluting plants.

Overall, this paper contributes to several strands of literature. The key contribution in this paper is assessing how climate policy uncertainty affects corporate decisions on environmental performance. One major challenge is to measure CPU. I overcome this challenge by employing the climate policy uncertainty index recently developed by Gavriilidis (2021). The other major challenge is to identify the causal relationship between CPU and toxic pollution. I address this problem using an instrumental variable, the number of Congressional voting on the topics related to climate change. This paper provides a novel result in the literature on the determinants of firm polluting behavior. It sheds light on the relation between climate policy uncertainty and firm's polluting behavior.

The paper contributes to the burgeoning literature on firms' environmental performance. Some recent papers study the role of shareholders in environmental performance (Bellon, 2020; Krueger, Sautner and Starks, 2020; Naaraayanan, Sachdeva and Sharma, 2019; Shive and Forster, 2020). For example, Bellon (2020) studies the impact of firms' private equity ownership on corporate environmental engagement. Brown, Martinsson and Thomann (2022) study emissions taxes and find that higher emission taxes lead to the increase in firms'

R&D spending. some studies find that firms' environmental performance is improved as the public's access to the emission information increases (e.g., Cordis, Hsu and Zhang (2021) and Konar and Cohen (1997)). In addition, studies find that media supervision also affects firms' polluting behaviors, e.g., Campa (2018) finds that plants emit less toxic chemicals if they located near newspapers' headquarters. The paper contributes to this strand of literature by identifying how macro-level climate policy uncertainty impacts firms' environmental behaviors.

This paper also augments the literature on policy and regulatory uncertainty. The majority of the literature focuses on the impact of political uncertainty on corporate investment (Durnev, 2013; Julio and Yook, 2012; Jens, 2017; Gulen and Ion, 2016), mergers and acquisitions (Bonaime, Gulen and Ion, 2018), and financing (Colak, Durnev and Qian, 2017). The existing studies concentrate on the real options theory. A few papers in finance study climate policy uncertainty. For example, Barnett, Brock and Hansen (2020) develop theoretical framework to address how climate uncertainty affects asset prices. Ilhan, Sautner and Vilkov (2020) suggest that climate policy uncertainty is priced in the option market. This study joins the burgeoning literature on policy uncertainty and finance, suggesting that unlike other types of uncertainty deferring investment, CPU leads to the adoption of the abatement technology and therefore, the reduction of toxic emissions.

The remainder of the paper is organized as follows. Section II presents a dynamic model and theoretically illustrates how climate policy uncertainty reduces firm pollution. Next, Section III describes the data and the variables used. Section IV presents the empirical results. Finally, Section V concludes.

II. Model: Abatement investment choices under climate policy uncertainty

Without uncertainty, firms make investment decisions purely following the Net Present Value (NPV) rule: invest when the present value of the project exceeds the cost of the project; reject, otherwise. However, if the investment is irreversible and undertaken under uncertainty, the firms may consider the option value of waiting in addition to the NPV of the project (Dixit and Pindyck, 1994; Bernanke, 1983; Rodrik, 1991).

In this section, I develop a dynamic model to derive the implications of climate policy uncertainty on firms' abatement investment choices based on the classical real options theory, while taking the compliance cost incurred by the polluting firms for each unit of pollution into consideration.

To simplify the analysis, I assume that the firm produces a single product through the polluting process. Reducing pollution is costly. To reduce its compliance cost, the firm can adopt the abatement technology. Suppose the installation of the abatement technology costs capital I. The firm emits X units of pollution without any emission reduction practice for the output amount Q. I assume the output level is fixed, i.e., $Q_t = Q$. To produce the quantity of Q output, the firm's realized emission is X without any emission reduction; $X - a$ with emission reduction. a is the firm's chosen abatement level. Assume the abatement cost per unit of emission reduction is constant, m. The firm's cost comes from the input, abatement, and compliance cost.

The compliance cost is set by the regulator. I denote the compliance cost per unit of emission as τ. τ is assumed to be represented by a geometric Brownian motion with positive drift α_τ and variance rate σ_τ. Climate policy uncertainty is represented by σ_τ:

$$d\tau = \alpha_\tau \tau dt + \sigma_\tau \tau dz_\tau, \;\; where \;\; dz_\tau = \epsilon\sqrt{dt}, \;\; \epsilon \sim N(0,1). \tag{1}$$

To simplify the model, I assume that the production process remains the same and the prices of the output (P) and input (C) are constant over time. To produce the amount of output Q, the amount of input N is needed. Therefore, at a given time, the profit function is $\pi(\tau)_1 = PQ - CN - ma - \tau(X - a)$ with abatement, and $\pi(\tau)_0 = PQ - CN - \tau X$ without abatement. Therefore, the value of the abatement investment, $v(\tau) = \tau a - ma$, is measured by the decrease in cost due to the abatement activities.

The present value of the investment over all future time periods is

$$V(\tau) = \int_T^\infty [\tau a e^{\alpha_\tau (t-T)} - ma] e^{-\rho(t-T)} dt, \tag{2}$$

where ρ is the discount rate. The present value can be written as

$$V(\tau) = \frac{\tau_T a}{\delta} - \frac{ma}{\rho}, \tag{3}$$

where $\delta = \rho - \alpha_\tau$. The parameter δ is defined as the difference between the firm's cost of capital and the drift rate of the compliance cost. It is necessary that $\delta > 0$ for the option to invest in abatement technology to be exercised. I solve for the trigger compliance unit cost following Dixit and Pindyck (1994). Denote the option value as a function of compliance cost per unit of emission, $F(\tau)$. Let ρ be the firm's discount rate. $\rho F(\tau)dt = E[dF(\tau)]$, indicating that over the interval dt, the rate of return of the option to invest should equal the expected rate of its capital appreciation. Given the boundary conditions, the function of $F(\tau)$ can be reduced to the form $F(\tau) = A\tau^\beta$. Apply Ito's lemma, we have

$$\frac{1}{2}\sigma_\tau^2 \beta(\beta - 1) + \alpha_\tau \beta - \rho = 0. \tag{4}$$

from which we can infer that keep everything else are equal, when σ_τ increases, β decreases.

At the trigger compliance cost, the value of the option to invest equals the net value of the investment $F(\tilde{\tau}) = V(\tilde{\tau}) - I$. The trigger cost is $\tilde{\tau}$ (derivation in Appendix section A):

$$\tilde{\tau} = \frac{\beta}{1+\beta} \, \frac{\delta}{a} \, [\frac{ma}{\rho} + I]. \tag{5}$$

Taking the partial derivative of $\tilde{\tau}$ with respect to β.

$$\frac{\partial \tilde{\tau}}{\partial \beta} = \frac{1}{(1+\beta)^2} \, \frac{\delta}{a} \, [\frac{ma}{\rho} + I] \geq 0. \tag{6}$$

Clearly, the first derivative of $\tilde{\tau}$ with respect to β is non-negative. From Equation 4, β decreases as climate policy uncertainty (σ_τ) increases. The increase in uncertainty leads to the decrease of β. Therefore, the trigger cost of compliance decreases. It indicates that after taking compliance cost into consideration, the higher the climate policy uncertainty, the more adoptions of the abatement technology to reduce emissions and avoid the future regulatory costs.

III. Data, sample, and empirical strategy

A. Data

A.1. Measure of climate policy uncertainty

Measuring climate policy uncertainty is one of the challenges the paper faces. To overcome the challenge, this paper uses the text-based macro-level measure of climate policy uncertainty (CPU index) recently developed by Gavriilidis (2021)[2]. He measures climate policy uncertainty as follows. He first searches for articles in eight leading US newspapers containing the terms (“uncertainty” or ”uncertain”) and (“carbon dioxide” or “climate” or “climate risk” or “greenhouse gas emissions” or “greenhouse” or “CO2” or “emissions” or “global warming” or “climate change” or “green energy” or “renewable energy” or “environmental”) and (“regulation” or “legislation” or “White House” or “Congress” or “EPA” or

[2]The data of climate policy uncertainty index is available at https://www.policyuncertainty.com/.

"law" or "policy" (including variants such as "uncertainties", "regulatory", "policies", etc.) from January 2000 till March 2021. The eight newspapers are: Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today, and the Wall Street Journal. For each newspaper, he scales the number of relevant articles per month with the total number of articles during the same month. Next, these eight series are standardized to have a unit standard deviation and then averaged across newspapers each month. Finally, the averaged series are normalized to have a mean value of 100 for the period 2000:M1-2021:M3. The index of CPU is a monthly index. I average it over 12 months each year to make it annually.

A.2. EPA data

To obtain toxic chemical emissions and the related data, I exploit three databases from the EPA, which I merge using their administrative identifiers. The first data source of emission comes from the Toxic Release Inventory (TRI). The database is constructed following Section 313 reporting requirements of the 1986 Emergency Planning and Community Right-to-Know Act (EPCRA). It provides self-reported toxic emission data and tracks the releases of 770 chemicals that threat human well-being and the environment. It also includes physical locations of plants, and parent companies' names and identifiers by the EPA. The second database is drawn from the EPA's Enforcement and Compliance History Online (ECHO) system. The ECHO system incorporates Federal Enforcement and Compliance (FE&C) from the Integrated Compliance Information System (ICIS). It tracks civil, judicial, and administrative EPA enforcement cases since 1980. Enforcement cases may result in monetary penalties. Firms could incur compliance cost to resolve the environmental violations. The third and final database is the EPA's Pollution Prevention (P2) database, which provides information on firms' production and abatement activities[3].

[3]The above-mentioned three major databases from the EPA are widely used in the existing studies, e.g., Bellon (2020, 2021); Chu, Guo, Zhao and Zheng (2021); Campa (2018); Cordis et al. (2021); Levine et al. (2019); Hamilton (1995)

There is no existing linkage between the administrative identifiers of the EPA databases and Compustat. Therefore, I perform fuzzy matching steps using company names to connect the environmental databases from the EPA to the firms in Compustat. To ensure the accuracy and matching quality, I manually check each matching pair of facility in the EPA databases and firms in Compustat.

B. Environmental variables construction

The main measure of toxic emissions used in this paper is toxic_release, which is the total weight of the on-site toxic chemical released (including air emissions, water discharges, underground injection, and etc.) aggregated at both facility- and firm- levels. I also count the number of toxic facilities reported to TRI by each firm in a given year. To account for skewness, I use the natural logarithm of these variables.

To measure production and abatement activities, I use the environmental variables from the EPA's Pollution Prevention (P2) database. First, I obtain the variable production_ratio, which is the ratio of the output at time t over the output at time t-1 from which the chemical is used. The variable is measured at chemical level. I aggregate it at both the facility- and firm- levels. Second, I construct source_reduction from the P2 database, to measure facilities' abatement activities, which reduce toxic release at the source. Under the Pollution Prevention Act of 1990 (PPA), the EPA collects information to track industry progress in reducing waste generation and moving towards safe waste management alternatives. Source_reduction measures year-to-year changes in releases. It quantifies the pollution prevention efforts that facilities have taken to prevent pollution and reduce the amount of toxic chemicals entering the environment.

C. Sample

The sample period is from 2000 through 2020. I exclude facility observations in the TRI dataset that report zero toxic emission across all years in the sample periods. The final sample of firms consists of 8,022 firm-year observations and 731 unique firms. The facility sample consists of 39,042 facility-year observations and 4,009 unique facilities. In the facility-chemical sample, there are 195,789 facility-chemical-year observations and 31,906 unique facility-chemical observations. The summary statistics are reported in Table I.

D. *Empirical strategy*

I first estimate the effect of climate policy uncertainty on firm toxic releases and the number of toxic facilities using the following specification:

$$Y_{i,t} = \alpha_i + \beta lnCPU_{t-1} + \gamma X_{i,t-1} + \delta Z_{t-1} + \epsilon_{i,t}, \tag{7}$$

where $Y_{i,t}$ represents the pollution variable of firm i in year t, including toxic emissions (ln(toxic_release)) and the number of toxic facilities (ln(N of toxic plants)). α_i is the firm fixed effects. $lnCPU_{t-1}$ is the measure of climate policy uncertainty in year *t-1*. $X_{i,t-1}$ is a vector of the control variables, including firm size, age, Tobin's q, ROA, capital investment, R&D, tangibility, leverage, cash flows. Z_{t-1} is a macro-level control, GDP growth.

I also estimate the facility-level specification as below:

$$Y_{i,j,t} = \alpha_{i,j} + \beta lnCPU_{t-1} + \gamma X_{i,t-1} + \delta Z_{t-1} + \epsilon_{i,j,t}, \tag{8}$$

where $Y_{i,j,t}$ is the pollution variable of facility j of firm i in year t. $\alpha_{i,j}$ is the firm-facility fixed effects. $lnCPU_{t-1}$ is the measure of climate policy uncertainty in year *t-1*. $X_{i,t-1}$ and Z_{t-1} are same as in Equation 7.

IV. Results

A. *Main results*

A.1. Firm-level evidence

I first examine the impact of climate policy uncertainty on pollution at the firm level, using the specification in Equation 7. Table II presents the results. Columns (1) and (2) display the results on toxic emissions. In Column (1), I include firm fixed effects but exclude the control variables. The coefficient estimate on $lnCPU$ is -0.579 and statistically significant at 1% level with a *t-statistic* of -5.16. In Column (2), I add the firm-level control variables, including firm size, age, Tobin's q, ROA, capital investment, R&D, tangibility, leverage, cash flows, and macro-level control, GDP growth to the regression. The magnitude of the coefficient of $lnCPU$ is -0.532 with a *t-statistic* of -4.28. These results suggest that higher climate policy uncertainty leads to pollution reductions.

Next, I examine whether CPU has an impact on firms' closures of the toxic facilities. In Column (3), I include firm fixed effects. The magnitude of the coefficient of $lnCPU$ is -0.05 with a *t-statistic* of -3.74. In Column (4), the firm-level control variables are added. The magnitude of the coefficient of $lnCPU$ is -0.052 and the coefficient is statistically significant at 5% level. The regression outcomes suggest that the increase of climate policy uncertainty leads to the closure of toxic plants. Putting together, we can infer that firm polluting behavior is affected by the macro-level climate policy uncertainty and firms reduce toxic emissions and close the toxic plants when CPU increases.

A.2. Facility-level evidence

Next, to corroborate the firm-level evidence, I investigate the facility-level data using the specification in Equation 8. Specifically, I include the same set of firm-level and macro-level control variables as in Table II but aggregate toxic releases at facility-level instead of firm-level. Table III displays the OLS regression results and the first-difference regression results.

I use facility fixed effects and cluster the standard errors at facility and year level in the test presented in Column (1) The magnitude of the coefficient of *lnCPU* is -0.431 with a *t-statistic* of -4.24, suggesting that CPU makes firms significantly reduce toxic releases at the facility level. The regression result of Column (2) in which I control for firm fixed effects and cluster standard errors at firm and year level remains consistent with the result in Column (1). The magnitude of the coefficient of *lnCPU* is -0.386 with a *t-statistic* of -4.05. Column (3) shows the first-difference estimation outcomes. The coefficient of *D.lnCPU(t-1)* remains negative and statistically significant at 10% level. Overall, the negative effects of CPU on the reduction of toxic emission become smaller at the facility-level relative to those at the firm-level. It could be a result of firms' closures of some toxic-releasing facilities.

A.3. Greenhouse gas emission

In this subsubsection, I restrict the pollution to greenhouse gas emissions. I conduct the analyses at both facility-level and chemical-level. The data on greenhouse emission provided by the EPA is limited as we can infer from the sample size reduction. Exploring the 1,885 facility-year observations, I find that CPU reduces greenhouse gas emissions (in Column (1) of Table IV). One unit increase in *lnCPU* leads to 0.12 unit reduction in *ln(GHG emission)*, with a *t-statistic* of -2.40.

Next, I examine the effects of CPU on greenhouse gas emissions at the chemical-level. I present the regression results in Columns (2) and (3) of Table IV. The magnitude of the coefficient of *lnCPU* is -0.16 with a *t-statistic* of -2.60 when I control for facility fixed effects and cluster standard errors at facility and year level. The result remains remarkably stable if I switch to facility-chemical fixed effects and cluster standard errors at facility-chemical and year level. Table IV provides evidence that greenhouse gas emission is affected by climate policy uncertainty and it declines while CPU increases.

A.4. Chemical-level evidence

I use toxic emission data which is either aggregated at the firm-level or at the facility-level above. A potential problem of aggregation is that firms can reduce less toxic chemical emissions but increase more toxic chemical releases. If this is the case, aggregating chemical emissions could lead to the misinterpretations of how CPU affects firms' polluting behaviors, since the composition changes of the chemicals released are missed by the aggregation. To mitigate this concern, I conduct the regressions at the facility-chemical-level. The results are presented in Table V. In Column (1), the dependent variable is total release amount of a toxic chemical. The coefficient estimation of *lnCPU* remains negative and significant. Using chemical-level data, the implication of CPU on firm pollution does not change. Besides the emission of each toxic chemical, I also specify the pollution path into air emission, water release, and ground injection. The results are reported in Columns (2) to (4) of Table V. Interestingly, I find that CPU negatively affects toxic emissions into the air. However, it does not significantly change the toxic chemical releases into water and ground.

B. Instrumental variable approach

A potential concern about the climate policy uncertainty index is endogeneity. Although I include a set of firm-level and aggregate-level variables to control for investment opportunities and economic conditions in the analyses, the effect of climate policy uncertainty on firm pollution may be confounded by other unobserved factors. In this subsection, I adopt the instrumental variable strategy to further ease the concern.

Specifically, I use the number of the Congressional voting on the topics related to climate change in a year as an instrument for the climate policy uncertainty index. Since the number of the Congressional voting is independent from macroeconomic conditions, it can serve as an instrumental variable for the CPU index, to disentangle the influence of climate policy uncertainty from other economic factors on toxic emissions. To construct the Congressional voting variable, I obtain the data on the U.S. Senate and the House of Representatives roll-call votes from the Congress.

I estimate the main model using the Congressional voting on topics related to climate change as an instrument for the aggregate climate policy uncertainty index. The results of the two-stage least square estimation are reported in Table VI.

Panel A of Table VI reports the regression results at the firm-level. Column (1) displays the first-stage regression results. Congress_voting positively associates with climate policy uncertainty. The *T-statistic* of the coefficient on Congress_voting is 3.69. The first-stage *F-statistic* is 13.65, suggesting that the instrumental variable is not a weak IV. Columns (2) and (3) present the results on toxic release and the number of toxic facilities, respectively. The magnitudes of the coefficients of $lnCPU$ in the IV regressions double the magnitudes of the coefficients of $lnCPU$ in the OLS estimations. The second-stage results suggest that the climate policy uncertainty leads to the reductions of firms' toxic emissions and the declines of the number of toxic plants. In Columns (4) and (5) of Panel B, I present the facility-level evidence. Using the instrumented $lnCPU$, I find that firms significantly reduce toxic emissions at the facility level when the climate policy uncertainty increases. The magnitude of the coefficient of the instrumented $lnCPU$ is twice of that in the OLS regression. The *F-statistic* is 14.47, exceeding 10, which is a typical threshold for a strong IV.

In Panel C of Table VI, I report the regression results at the facility-chemical level. The coefficients of the instrumented climate policy uncertainty remain negative and significant for total toxic releases and the releases into the air. It is consist with the findings in Table V. The results on toxic releases into water and ground are statistically insignificant. The first-stage F statistics are 11.32. Generally, the findings are robust to the instrumental variable approach.

C. Abatement activities and source reduction

In this subsection, I report the direct evidence that the pollution reduction is a result of the increased abatement activities. I focus on process-related abatement activities at the source, which consist of modifying how the product is made to reduce pollution. For example, firms reduce the packaging or the chemicals contained in the product or reuse the chemicals. According to the EPA, source reduction is the most favorable practice as it reduces pollution at the origins.

Table VII reports the OLS regression results. The dependent variable is the percentage of source reduction comparing with the previous year. Columns (1) and (2) report the facility-level regression result. One unit increase in $lnCPU$ leads to 0.308 units source reduction in the following year. I also employ the first-difference regression. The results are reported in Column (2). All variables are in the first-difference format in the estimation. The coefficient magnitude of $\Delta lnCPU$ is 0.814 with a *t-statistic* of 1.74. Next, examining the facility-chemical level evidence, I find a similar pattern that firms increase source reduction through abatement activities during the heightened CPU periods. The coefficient magnitude of $lnCPU$ in the level regression in Column (3) is 0.22 and statistically significant at 5% level. The evidence from the first-difference regression is consistent. Overall, the results support the model implication that source reductions are enlarged through the increased abatement activities when the climate policy uncertainty rises. As a result, toxic emissions are reduced.

D. Mechanisms

D.1. EPA regulatory activities

The results suggest that firms reduce toxic emissions through increasing abatement activities when climate policy uncertainty increases. However, a question remains: why does climate policy uncertainty, unlike other uncertainties that defer firm investment, increase abatement activities? Dorsey (2019) finds that less pollution was reduced and fewer pollution control investment was made if the plants have lower probabilities of being regulated. In this subsubsection, I explore whether the EPA regulation intensity can explain why firms reduce environmental pollution when facing high CPU. I estimate the following regression,

$$
\begin{aligned}
Y_{i,j,t} = \alpha_{i,j} + \beta CPU\_high_{t-1} \times Toxic\_release_{i,j,t-1} + \lambda CPU\_high_{t-1} \\
+ \delta Toxic\_release_{i,j,t-1} + \gamma X_{i,t-1} + \delta Z_{t-1} + \epsilon_{i,t},
\end{aligned} \tag{9}
$$

where $Y_{i,j,t}$ represents the EPA regulation variable of facility j of firm i in year t, including the dummy variables of the EPA penalty, violation and enforcement as well as the continuous variable, compliance costs (*ln(compliance cost)*. $\alpha_{i,j}$ is the facility fixed effects. CPU_high_{t-1} is a dummy variable indicating whether CPU is above (equals 1) or below (equals 0) the sample median. $X_{i,t-1}$ is a vector of control variables, including firm size, age, Tobin's q, ROA, capital investment, R&D, tangibility, leverage, cash flows. Z_{t-1} is a macro-level control, GDP growth. I estimate the Logit model if the dependent variables are the dummy variables (i.e., penalty, violation and enforcement). The OLS regression is estimated when the dependent variable is *ln(compliance cost)*. I estimate the regression at the facility level since the facility evidence is not affected by the closure of toxic plants.

Investigating the environmental regulatory activities, I provide the direct evidence on how CPU affects firms' regulatory costs. The interaction terms $CPU\_high \times Toxic\_release$ have consistent positive and statistically significant coefficient across the four regressions. The results suggest that polluting firms are more likely to incur penalty, EPA violation and enforcement, and have higher compliance costs when CPU is high. Furthermore, in Table AII, I examine whether EPA increases inspection intensity during the heightened CPU periods. The Logit model regression results at both firm- and facility-level indicate that EPA is more likely to inspect polluting facilities when CPU is high. The evidence together suggests that a sticker regulatory standard is imposed during the high CPU periods, which induces firms to reduce emissions.

D.2. Institutional ownership

A survey by Krueger et al. (2020) suggests that institutional investors believe that climate regulatory risks have begun to materialize and have significant financial implication for firms. However, climate policy uncertainty makes it hard for investors to quantify the impact of future regulation on polluting firms. Existing studies suggest that institutional investors punish polluting firms through withdrawing the holdings of the company (Kim, Hong, Wang and Yang, 2019). Moreover, Matsumura, Prakash and Vera-Muñoz (2013) find that polluting firm value decreases as the carbon emissions increase.

The question that whether climate regulatory uncertainty leads to the punishment by investors remains unanswered. Uncertainty that results from government policy and regulatory shocks is largely exogenous and non-diversifiable, which makes CPU difficult to be hedged by investors. In turn, investors' incentives to withdraw capital from polluting firms may increase. In this subsubsection, I investigate how climate policy uncertainty affects highly polluting firms' institutional ownership, which may partially explain the reason why firms reduce emissions and close polluting facilities under high climate policy uncertainty. Specifically, I estimate the following regression,

$$\begin{aligned} Y_{i,t} = \alpha_i + \beta lnCPU_{t-1} \times Toxic\_high_{i,t-1} + \lambda lnCPU_{t-1} \\ + \delta Toxic\_high_{i,t-1} + \gamma X_{i,t-1} + \delta Z_{t-1} + \epsilon_{i,t}, \end{aligned} \tag{10}$$

where $Y_{i,t}$ is the institutional holdings of firm i in year t or a dummy variable, *InstOwn_low*, indicating whether firm i has relatively lower institutional ownership comparing with its industry peers in a given year. $Toxic\_high_{t-1}$ is a dummy variable indicating whether a firm's pollution is above the industry-year median. $lnCPU_{t-1}$ is the measure of climate policy uncertainty in year *t-1*. α_i is the firm fixed effects. $X_{i,t-1}$ is a vector of control variables, including firm size, age, Tobin's q, ROA, capital investment, R&D, tangibility, leverage, cash flows. Z_{t-1} is the macro-level control, GDP growth.

Table IX presents the regression results. Columns (1) and (2) are the OLS regression estimations. The negative and significant coefficient of the interaction term of $lnCPU_{t-1}$ and $Toxic\_high_{t-1}$ in Column (1) suggests that highly polluting firms experience more institutional ownership reduction when CPU is high. Column (2) displays the results of the first-difference regression, in which the corresponding independent and control variables are also in the first-difference format. The first-difference estimation outcome is consistent with that of the OLS regression, suggesting that CPU leads to institutional ownership reduction in the highly polluting firms. Column (3) presents the Logit regression estimation, in which the dependent variable is a dummy variable, *InstOwn_low*, to indicate whether a firm's institutional ownership is lower than the industry-year median. I find that high polluting firms are more likely to have lower institutional ownership when climate policy uncertainty is high. The coefficient of *InstOwn_low* is significant at 1% level with a *t-statistic* of 2.79. The evidence on institutional ownership suggests that highly polluting firms are punished by institutional investors through capital withdrawn under high CPU.

E. *Heterogeneous effects*

I argue that climate policy uncertainty leads to higher probabilities of incurring penalties, EPA violations and enforcement, having larger compliance costs, and experiencing a reduction in institutional ownership for highly polluting firms. Therefore, CPU motivates firms to adopt abatement technology and thereby, reduce toxic emissions. Installing the abatement technology is costly. Existing studies suggest that firms' financial conditions affect its environmental performance (Levine et al., 2019; Xu and Kim, 2022; Bartram, Hou and Kim, 2022). If a firm is financially constrained, it may have limited ability to invest in the abatement technology and therefore, have limited reduction of toxic emissions.

To examine the heterogeneous effects of financial constraints on the impact of CPU on firm pollution, I interact CPU with the financial constraint status. Specifically, I measure financial constraint status using the HP index (Hadlock and Pierce, 2010). I rank the firms and assign firms into the financially more constrained (less constrained) group if a firm's HP index is above (below) the industry-year median. The regressions are conducted at the firm level. The results, in Columns (1) and (2) of Table X, suggest a positive and significant interaction effect of CPU and financial constraints. It supports that although CPU leads to the reduction in toxic emissions and the closure of toxic facilities, financial constraints weaken the influence of CPU.

Next, studies suggest that although uncertainty is identical to all firms, the perception of uncertainty for people varies, depending on individual's characteristics. Towards this end, examining the heterogeneous effects of CEO age and tenure could provide interesting evidence. On the one hand, younger CEOs and CEOs with short tenure may have limited experience dealing with climate policy uncertainty. On the other hand, these CEOs are probably more concerned about their reputation in the labor market. Having EPA penalties, violations, enforcement or experiencing a large reduction in institutional holdings does not add values to their managerial careers.

Therefore, to test this hypothesis, I interact CPU with the indicator variables of CEO age and CEO tenure, respectively[4]. The results of the interaction regressions are presented in Columns (3) to (6) in Table X. Interestingly, I find that younger CEOs and CEOs with short tenure enhance the influence of CPU on toxic emissions, but not the closure of toxic facilities.

Overall, the effects of CPU on the reduction of toxic emissions are weakened in financial constrained firms, but reinforced in the firms with younger CEOs and CEOs with short tenure.

[4]CEO_young is a dummy variable which is set to be 1 if a firm has a CEO younger than the industry-year median CEO age and zero, otherwise. CEO_short_tenure is an indicator variable which takes value 1 if the CEO of a firm has shorter tenure relative to the industry-year median CEO tenure and zero, otherwise.

F. Other outcomes

To better understand the influence of CPU, I explore whether climate policy uncertainty affects other corporate outcomes, i.e., stock return, *Tobin's Q*, cash holdings, number of analysts following, stock volatility, and analyst forecast dispersion. The results are presented in Table XI. First of all, I find that climate policy uncertainty is related to the declines in firm's stock returns and polluting firms' valuations. Firms' cash holdings also decrease when CPU rises. Furthermore, Climate policy uncertainty relates to the reduction of the number of analysts following the polluting firms. I also examine the effects of CPU on stock volatility and analyst forecast dispersion. The results, in Columns (5) and (6), show that climate policy uncertainty is associated with the increases stock return volatility and analyst forecast dispersion. Employing the first-difference regressions, I find consistent evidence.

G. Robustness checks

G.1. Is the impact of CPU on pollution driven by the change in production?

First of all, the results above suggest that climate policy uncertainty causes firms to adopt abatement technology and reduce emissions. The reduction in toxic releases during the heightened CPU periods could be driven by the decreases in production activities. To mitigate this concern, I use the production ratio variable provided by the TRI database from the EPA to examine whether the firms and facilities reduce production activities when CPU is high. Specifically, production ratio captures the growth rate of the output whose production results in toxic chemical releases.

The results on production are reported in Table XII. Column (1) presents the firm-level evidence. The coefficient estimate on *lnCPU* is tiny and statistically insignificant. Column (2) displays the facility-level regression evidence in which I control for facility fixed effects and cluster standard errors at facility and year level. Column (3) is the facility-chemical level estimation in which I control for facility-chemical fixed effects and cluster standard errors at facility-chemical and year level. In general, the coefficient estimates of $lnCPU$ are statistically insignificant in the regressions and the magnitudes are tiny. The results on production_ratio suggest that the decrease of toxic emissions is not a result of the reduction in the production activities.

G.2. Climate policy uncertainty versus non-climate policy uncertainty

I argue that climate policy uncertainty motivates firms to reduce pollution. However, the results could instead be driven by a general fear of uncertainty. To alleviate this concern, I include non-climate policy uncertainty, i.e., economic policy uncertainty (EPU) to the baseline regressions to check whether it has similar influence on firm pollution. If the results are driven by the general fear of policy uncertainty, economic policy uncertainty should also have negative effects on toxic emissions.

I use the economic policy uncertainty index developed by Baker et al. (2016). EPU index is a continuous time-varying country-level variable. The EPU index is a weighted average of four components. The first component is based on a count of newspaper articles in 10 leading U.S. newspapers, articles including at least one key policy term (i.e., white house, federal, congress, regulation, and so on), at least one economic term (i.e., economic and economy), and at least one uncertainty term (i.e., uncertainty and uncertain). The second component measures uncertainty about future changes in the tax code. The third and the fourth components are based on dispersion of economic forecasts about the consumer price index (CPI) and government spending (purchases by the federal, state, or local government). Among the four components, the first component is the most weighted one. I present the trends of EPU and CPU in Figure 1, from which We can clearly infer that CPU and EPU are distinct from each other.

The results of regressions are presented in Table XIII. The firm-level evidence is presented in Columns (1) and (2).The facility-level evidence is reported in Column (3). The chemical-level results are reported in Columns (4) and (5). The dependent variables examined in

Columns (1) and (2) are toxic_release and the number of toxic plants, respectively. First of all, additionally controlling for EPU does not change the baseline results. The coefficients of *lnCPU* remain negative and significant in both regressions and the magnitudes are close to those in Table II. Secondly, the coefficients of EPU are not statistically significant across the regressions. The magnitudes of EPU are small comparing with those of CPU. For example, in Column (1), the coefficient of CPU is -0.531 with a *t-statistic* of -4.30, while the coefficient of EPU is 0.038 and statistically insignificant. I next turn to the facility- and chemical-level evidence. Consistently, the coefficients of *lnCPU* remain negative and statistically significant. However, the coefficients of *lnEPU* are statistically insignificant and the magnitudes of the coefficients are tiny. Therefore, the results that firms reduce toxic emissions and close toxic plants when CPU rises are not driven by a general fear of uncertainty.

G.3. Controlling for climate-related policy "certainty"

Climate policy uncertainty is a measure of regulatory volatility. The results above have shown that the volatility in regulation affects firms' polluting behaviors. In reality, besides the uncertainty on climate policy, there ought to be "certainty" of the regulations, which should affect firm pollution as well. Therefore, in this subsubsection, I investigate whether the effect of climate policy uncertainty is robust to the addition of the regulatory "certainty".

To measure climate policy "certainty", I explore the states' Climate Change Adoption Plans (CCAP). In the U.S., some states have begun to prepare for the climate changes. This planning process typically results in a document called adaptation plan. I use the state's CCAP status to measure the regulatory "certainty" in a firm's headquarter state. Specifically, I construct a binary variable, CCAP_status, which takes value 1 in the years after the firm's headquarter state has adopted such a plan, and 0 before a state carried out such plan as well as for the states have never published such plan so far.

The results are reported in Table XIV. Columns (1) and (2) report the OLS regression results. After controlling for CCAP_status, the coefficient estimates of *lnCPU* remain negative and significant. The coefficients of CCAP_status are also negative and significant, suggesting the effectiveness of Climate Change Adoption Plans in reducing toxic emissions and closing toxic release facilities among the polluting firms. Columns (3) to (5) present the IV regression results, in which I use the Congressional voting on the topics of climate change to instrument *lnCPU*. The first-stage F-statistic is 13.77. The IV regression results remain consistent as the OLS results. The coefficient estimates of instrumented *lnCPU* are negative and statistically significant after controlling for the "certainty" on regulation in the firm's headquarter state. Overall, it suggests that climate regulatory volatility negatively impact firm toxic emissions and the closure of toxic release facilities even after controlling for the regulatory "certainty".

V. Conclusion

As public awareness of climate change increases, future regulatory interventions of emissions to protect the global climate cause uncertainty of the environment in which the U.S. firms operate. In this paper, I examine the impact of macro-level climate policy uncertainty on firms' polluting behavior. The paper develops a dynamic model suggesting that firms are more likely to invest in abatement technology to reduce toxic emission when they face higher CPU. Contrary to the classic real options theory that uncertainty defers investment, I demonstrate that under climate policy uncertainty, the regulatory cost of emission overweights the option value of waiting. Therefore, it encourages the abatement activities when CPU is high.

The empirical evidence confirms the model implication. I find that firms reduce toxic emissions at the firm-, facility-, and chemical-level when CPU increases. I also find that firms are more likely to close polluting facilities during the heightened CPU periods. I confirm that these findings are not driven by the decrease in production activities. Further analyses reveal that, when CPU increases, highly polluting firms are more likely to incur EPA penalties, violations, enforcement, and have higher compliance costs. I also find that highly polluting firms experience institutional ownership reductions when CPU is high.

Additionally, CPU is associated with lower stock returns, firm valuations, fewer analysts following, higher stock return volatility, and analyst forecast dispersion. Lastly, employing the Congressional voting on the topics related to climate change in each year as an instrumental variable for CPU, I argue that the impact of CPU on toxic releases is likely to be causal.

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Figure 1: **Measure of climate policy uncertainty**

Gavriilidis (2021) measures climate policy uncertainty as follows. He searches for articles in eight leading US newspapers containing the terms ("uncertainty" or "uncertain") and ("carbon dioxide" or "climate" or "climate risk" or "greenhouse gas emissions" or "greenhouse" or "CO2" or "emissions" or "global warming" or "climate change" or "green energy" or "renewable energy" or "environmental") and ("regulation" or "legislation" or "White House" or "Congress" or "EPA" or "law" or "policy" (including variants such as "uncertainties", "regulatory", "policies", etc.) from January 2000 till March 2021. The eight newspapers are: Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today and the Wall Street Journal. For each newspaper, he scales the number of relevant articles per month with the total number of articles during the same month. Next, these eight series are standardized to have a unit standard deviation and then averaged across newspapers by month. Finally, the averaged series are normalized to have a mean value of 100 for the period 2000:M1-2021:M3. The following figure depicts the trend of CPU (in blue) monthly during the sample period from 2000 to 2020. The orange line represents the trend of EPU index during the same period.

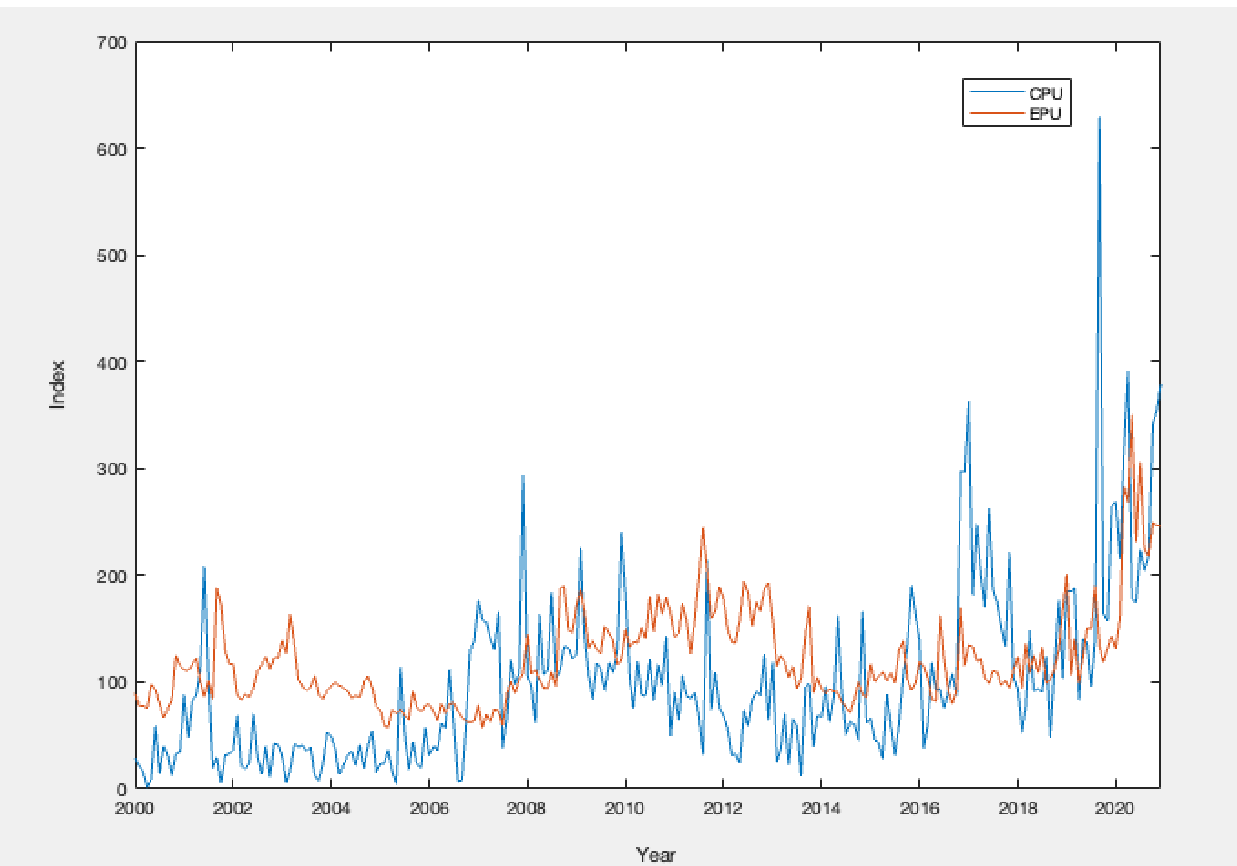

Figure 1: Climate policy uncertainty and economic policy uncertainty

Table I: **Summary Statistics**

This table reports the summary statistics for the main variables used in the analyses. All variables are defined in the Table AI. The sample consists of all nonfinancial and nonutility firms during 2000 to 2020. There are 8,022 firm-year observations and 731 unique firms in the main sample. The facility sample has 39,042 observations and 4,009 unique facilities. The chemical sample has 195,789 observations and 31,906 unique facility-chemical observations.

variable	N	Mean	STD	P25	Median	P75
Firm-level variables						
ln(toxic_release)	8,022	8.11	4.66	4.82	8.95	11.46
ln(N of toxic plants)	8,022	1.38	0.75	0.69	1.10	1.79
production_ratio	7,575	0.01	0.02	0.01	0.01	0.01
penalty_dummy	8,022	0.06	0.23	0.00	0.00	0.00
violation_dummy	8,022	0.06	0.23	0.00	0.00	0.00
ln(compliance cost)	8,022	0.37	1.84	0.00	0.00	0.00
Size	8,022	7.16	2.39	5.74	7.31	8.81
Cash flow	8,022	29.35	156.01	0.02	0.25	2.78
ROA	8,022	0.04	0.11	0.01	0.05	0.09
TQ	8,022	1.79	1.05	1.12	1.48	2.08
Leverage	8,022	0.26	0.18	0.12	0.25	0.37
R&D	8,022	0.03	0.04	0.00	0.01	0.03
Tangibility	8,022	0.29	0.17	0.16	0.25	0.38
Capex	8,022	0.05	0.04	0.02	0.04	0.06
ln(firm age)	8,022	3.24	0.75	2.71	3.37	3.93
annual_return	7,408	0.13	0.47	-0.14	0.09	0.33
ln(analysts)	7,558	1.88	0.99	1.10	2.08	2.71
stock_volatility	6,855	0.03	0.01	0.02	0.02	0.03
analyst_disp	6,133	0.08	0.21	0.01	0.02	0.06
InstOwn	7,133	0.70	0.26	0.57	0.76	0.89
Facility-level variables						
ln(toxic_release)	39,042	6.22	4.68	1.27	6.64	10.10
ln(GHG emission)	2,171	11.91	1.63	10.65	11.39	13.28
production_ratio	36,274	0.15	15.69	0.01	0.01	0.01
source_reduction	5,367	-0.95	5.51	-0.36	0.00	0.26
penalty_dummy	39,042	0.02	0.13	0	0	0
violation_dummy	39,042	0.02	0.12	0	0	0
ln(compliance cost)	39,042	0.06	0.52	0	0	0
Facility-chemical level variables						
ln(toxic_release)	195,786	4.75	4.07	0.18	4.67	8.19
ln(air)	195,786	4.06	3.78	0	3.47	7.09
ln(water)	195,786	0.72	1.94	0	0	0
ln(ground)	195,778	0.97	2.90	0	0	0
production_ratio	178,580	0.03	1.07	0.01	0.01	0.01
source_reduction	13,019	-0.56	3.18	-0.31	0	0.27
ln(GHG emission)	7,161	7.25	3.76	3.62	7.59	10.47
Macro-level variables						
lnCPU	8,022	4.31	0.66	3.58	4.44	4.83
lnEPU	8,022	4.73	0.29	4.48	4.71	4.95
GDP Growth	8,022	1.92	1.76	1.64	2.25	2.91
Congress_voting	8,022	5.40	4.90	1	6	11

Table II: **Climate policy uncertainty and pollution (Firm-level evidence)**

The table presents the OLS regression results. The dependent variables are ln(toxic_release) in Columns (1) and (2) and ln(N of toxic plants) in Columns (3) and (4). ln(toxic_release) is the natural logarithm of the total weight of on-site toxic chemical release (in pound), and measured at the firm level. ln(N of toxic plants) is the natural logarithm of the total number of toxic facilities a firm has in a given year. The independent variable of interest is lagged lnCPU. The sample period starts from 2000 to 2020. The control variables are firm size, ln(firm age), TQ, ROA, Capex, R&D, Tangibility, Leverage, Cash Flow, GDP Growth. All continuous variables are winsorized at 1st and 99th percentile. The regressions control fixed effects as shown in the bottom of the table. *T*-statistics are in parentheses. Coefficients statistically significant at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

VARIABLES	(1) ln(toxic_release)	(2) ln(toxic_release)	(3) ln(N of toxic plants)	(4) ln(N of toxic plants)
lnCPU(t-1)	-0.579***	-0.532***	-0.050***	-0.052**
	(-5.16)	(-4.28)	(-3.74)	(-2.74)
Size(t-1)		0.204***		0.034***
		(2.94)		(3.33)
ln(firm age)(t-1)		-0.989***		-0.080**
		(-3.48)		(-2.16)
MTB(t-1)		-0.001		-0.018**
		(-0.01)		(-2.67)
ROA(t-1)		0.345		-0.005
		(0.86)		(-0.10)
Capex(t-1)		0.181		0.144
		(0.19)		(1.12)
R&D(t-1)		0.590		0.096
		(0.23)		(0.32)
Tangibility(t-1)		0.793		0.110
		(1.30)		(1.11)
Leverage(t-1)		0.344		0.009
		(0.86)		(0.21)
Cash Flow(t-1)		0.000		0.000
		(0.81)		(1.23)
GDP Growth(t-1)		-0.091***		-0.007*
		(-2.87)		(-1.81)
Constant	10.641***	12.008***	1.618***	1.642***
	(21.79)	(15.31)	(27.78)	(15.82)
Observations	7,124	7,124	7,124	7,124
Adjusted R-squared	0.861	0.864	0.939	0.941
Firm FE	Yes	Yes	Yes	Yes
Cluster by Firm Year	Yes	Yes	Yes	Yes

Table III: **Climate policy uncertainty and toxic release (Facility-level evidence)**

The table presents the OLS regression results. The dependent variable is toxic release, which is the natural logarithm of the total weight of on-site toxic chemical release (in pound), and measured at the facility level. The independent variable of interest is lagged lnCPU. Panel A reports the OLS regression results. Panel B presents the first-difference regression results. The sample period starts from 2000 to 2020. There are 39,042 facility-year observations and 4009 unique facilities in the sample. The control variables are same as in Table II. All continuous variables are winsorized at 1st and 99th percentile. The regressions control fixed effects as shown in the bottom of the table. Standard errors are clustered at facility-year or firm-year level. *T*-statistics are in parentheses. Coefficients statistically significant at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	(1)	(2)	(3)
VARIABLES	ln(toxic_release)	ln(toxic_release)	D.ln(toxic_release)
lnCPU(t-1)	-0.431***	-0.386***	-0.209*
	(-4.24)	(-4.05)	(-1.86)
Size(t-1)	0.018	-0.060	0.001
	(0.45)	(-1.31)	(0.03)
ln(firm age)(t-1)	-0.159	-0.081	-0.105
	(-0.80)	(-0.37)	(-0.68)
MTB(t-1)	0.008	0.054	0.016
	(0.39)	(1.60)	(1.53)
ROA(t-1)	-0.001	-0.000	0.001
	(-0.03)	(-0.01)	(0.03)
Capex(t-1)	-0.007	-0.010	0.003
	(-0.04)	(-0.03)	(0.02)
R&D(t-1)	-1.064	-2.291	-0.737
	(-0.98)	(-1.51)	(-1.52)
Tangibility(t-1)	0.604*	0.839	0.231
	(1.98)	(1.44)	(1.12)
Leverage(t-1)	0.356*	0.412	0.052
	(1.87)	(1.49)	(0.60)
Cash Flow(t-1)	-0.000**	-0.000*	0.000
	(-2.11)	(-2.01)	(1.05)
GDP Growth(t-1)	-0.046*	-0.037	-0.035
	(-1.97)	(-1.36)	(-1.66)
Constant	8.396***	8.399***	-0.049
	(13.94)	(11.68)	(-1.65)
Observations	33,900	34,193	30,243
Adjusted R-squared	0.875	0.447	0.003
Facility FE	Yes		Yes
Cluster by Facility Year	Yes		Yes
Firm FE		Yes	
Cluster by Firm Year		Yes	

Table IV: **Climate policy uncertainty and greenhouse gas emission**

The table presents the OLS regression results. The dependent variable is the greenhouse gas emission, which is the natural logarithm of total weights of greenhouse gas emission reported to the EPA (in pounds). It is measured at the facility-level (in Column (1)) and the facility-chemical level (in Column (2) and (3)). The independent variable of interest is lagged lnCPU. The sample period starts from 2000 to 2020. The control variables are same as in Table II. All continuous variables are winsorized at 1st and 99th percentile. The regressions control fixed effects as shown in the bottom of the table. *T*-statistics are in parentheses. Coefficients statistically significant at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Facility-level	Chemical-level	
	(1)	(2)	(3)
VARIABLES	ln(GHG emission)	ln(GHG emission)	ln(GHG emission)
lnCPU(t-1)	-0.120**	-0.160**	-0.147**
	(-2.40)	(-2.60)	(-2.82)
Size(t-1)	0.050	-0.016	0.012
	(1.39)	(-0.28)	(0.23)
ln(firm age)(t-1)	0.026	0.147	0.140
	(0.29)	(0.91)	(0.92)
MTB(t-1)	0.051	0.111*	0.091**
	(1.28)	(2.17)	(2.88)
ROA(t-1)	0.082	-0.080	-0.102
	(0.39)	(-0.39)	(-0.48)
Capex(t-1)	-0.820	0.313	-0.244
	(-0.74)	(0.26)	(-0.25)
R&D(t-1)	5.165	-0.742	0.529
	(1.26)	(-0.26)	(0.25)
Tangibility(t-1)	-0.043	-0.030	-0.058
	(-0.33)	(-0.13)	(-0.29)
Leverage(t-1)	-0.052	-0.131	-0.144
	(-0.58)	(-1.05)	(-1.24)
Cash Flow(t-1)	0.000	-0.000***	-0.000*
	(0.68)	(-4.26)	(-2.19)
GDP Growth(t-1)	-0.042	-0.057	-0.048
	(-1.52)	(-0.94)	(-0.96)
Constant	11.952***	7.687***	7.438***
	(31.84)	(12.83)	(12.66)
Observations	1,885	6,168	6,133
Adjusted R-squared	0.971	0.224	0.967
Facility FE	Yes	Yes	
Cluster by Facility Year	Yes	Yes	
Facility-Chemical FE			Yes
Cluster by Facility-Chemical Year			Yes

Table V: **Climate policy uncertainty and toxic release (Chemical-level evidence)**

The table presents the OLS regression results. The dependent variables are reported at the top of each column. ln(toxic_release) is the natural logarithm of total weights of toxic chemical emission (in pounds). ln(air), ln(water), and ln(ground) are the natural logarithm of total weights of toxic chemical released into the air, water, and ground, respectively. The dependent variables are measured at facility-chemical level. The independent variable of interest is lagged lnCPU. The sample period starts from 2000 to 2020. There are 195,789 facility-chemical-year observations and 31,906 unique facility-chemical observations. The control variables are same as in Table II. All continuous variables are winsorized at 1st and 99th percentile. The regressions control fixed effects as shown in the bottom of the table. T-statistics are in parentheses. Coefficients statistically significant at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

VARIABLES	(1) ln(toxic_release)	(2) ln(air)	(3) ln(water)	(4) ln(ground)
lnCPU(t-1)	-0.096**	-0.102**	0.005	-0.057
	(-2.14)	(-2.46)	(0.12)	(-0.96)
Size(t-1)	0.015	-0.004	0.009	0.015
	(0.75)	(-0.19)	(0.69)	(1.02)
ln(firm age)(t-1)	-0.173**	-0.190**	-0.071	0.035
	(-2.34)	(-2.85)	(-1.10)	(0.33)
MTB(t-1)	0.006	0.010	-0.019	0.011
	(0.30)	(0.51)	(-1.69)	(0.65)
ROA(t-1)	0.044	0.158	-0.005	-0.075
	(0.35)	(1.35)	(-0.04)	(-0.67)
Capex(t-1)	0.063	0.016	-0.152	0.080
	(0.14)	(0.04)	(-0.69)	(0.21)
R&D(t-1)	0.653	0.043	1.633*	0.259
	(0.41)	(0.02)	(1.82)	(0.37)
Tangibility(t-1)	0.277*	0.173	0.020	-0.109
	(1.91)	(1.37)	(0.21)	(-0.85)
Leverage(t-1)	-0.045	-0.076	-0.091	0.202***
	(-0.53)	(-0.93)	(-1.65)	(3.23)
Cash Flow(t-1)	-0.000	0.000	0.000	-0.000
	(-0.67)	(0.90)	(0.26)	(-0.63)
GDP Growth(t-1)	0.002	-0.002	-0.008	0.020
	(0.23)	(-0.24)	(-0.83)	(1.22)
Constant	5.552***	5.219***	0.943***	0.861**
	(22.23)	(23.41)	(4.42)	(2.18)
Observations	150,460	150,460	150,460	150,452
Adjusted R-squared	0.914	0.912	0.856	0.881
Facility-Chemical FE	Yes	Yes	Yes	Yes
Cluster by Facility-Chemical Year	Yes	Yes	Yes	Yes

Table VI: **Instrumental variable approach**

The table presents the instrumental variable regression results. The regressions are performed at firm-, facility, and facility-chemical level, respectively. The dependent variables are toxic release and N of toxic plants. The instrumental variable is congressional voting, which is the number of congressional voting on the topic related to climate change each year. The independent variable of interest is lagged lnCPU. Panel A and B present the firm-level and facility-level evidence, respectively. The Cragg-Donald Wald F-statistics are reported at the bottom of the table. The sample period starts from 2000 to 2020. The control variables included in the regressions are same as in Table II. All continuous variables are winsorized at 1st and 99th percentile. The regressions control fixed effects as shown in the bottom of the table. *T*-statistics are in parentheses. Coefficients statistically significant at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Panel A: Firm-level			Panel B: Facility-level	
	(1)	(2)	(3)	(4)	(5)
VARIABLES	lnCPU(t-1)	ln(toxic_release)	ln(N of toxic plants)	lnCPU(t-1)	ln(toxic_release)
Congress_voting(t-1)	0.063***			0.062***	
	(3.69)			(3.80)	
lnCPU(t-1)		-1.047***	-0.103**		-0.828***
		(-3.90)	(-2.28)		(-5.36)
Observations	7,124	7,124	7,124	33,900	33,900
Adjusted R-squared	0.735			0.735	
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes		
Cluster by Firm Year	Yes	Yes	Yes		
Facility FE				Yes	Yes
Cluster by Facility Year				Yes	Yes
Cragg-Donald Wald F-statistics		13.65	13.65		14.47

	Panel C: Chemical-level				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	lnCPU(t-1)	ln(toxic_release)	ln(air)	ln(water)	ln(ground)
Congress_voting(t-1)	0.056***				
	(3.36)				
lnCPU(t-1)		-0.269**	-0.237**	-0.107	-0.048
		(-2.21)	(-2.21)	(-1.41)	(-0.63)
Observations	150,460	150,460	150,460	150,460	150,452
Adjusted R-squared	0.714				
Controls	Yes	Yes	Yes	Yes	Yes
Facility-Chemical FE	Yes	Yes	Yes	Yes	Yes
Cluster by Facility-Chemical Year	Yes	Yes	Yes	Yes	Yes
Cragg-Donald Wald F-statistics		11.32	11.32	11.32	11.32

Table VII: **Climate policy uncertainty and abatement activities**

The table presents the OLS regression results. The dependent variable is source_reduction, which measures the percentage reduction of toxic emission due to abatement activities. I focus on process related abatement activities, which consist of modifying how the product is made to reduce pollution. This approach to reducing pollution is the most favorable one as it reduces pollution at the source. I measure it at both facility and facility-chemical level. The independent variable of interest is lagged lnCPU. I use both OLS level regressions (in Columns (1) and (3)) and first-difference regressions (in Columns (2) and (4)). In first-difference regressions, the dependent variable, independent variable, and the control variables are all in the first-difference format. The sample period starts from 2000 to 2020. The control variables are same as in Table II. The regressions control fixed effects as shown in the bottom of the table. T-statistics are in parentheses. Coefficients statistically significant at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Facility-level evidence		Chemical-level evidence	
	(1)	(2)	(3)	(4)
VARIABLES	source_reduction	D.source_reduction	source_reduction	D.source_reduction
lnCPU(t-1)	0.308*	0.814*	0.220**	0.274*
	(1.93)	(1.74)	(2.46)	(2.03)
Observations	4,251	2,801	9,298	5,469
Adjusted R-squared	0.208	0.003	0.238	0.081
Controls	Yes	Yes	Yes	Yes
Fixed effects	Facility	Facility	Facility-Chemical	Facility-Chemical
Cluster by	Facility Year	Facility Year	Facility-Chemical Year	Facility-Chemical Year

Table VIII: **Climate policy uncertainty and EPA regulatory activities**

The table presents the results on EPA regulatory activities. Columns (1) to (3) are the Logit model regression results. Column (4) presents the OLS regression estimation. The dependent variables are reported at the top of each column. The independent variable of interest is the interaction between a dummy variable, CPU_high, and toxic_release. The regressions are performed at facility-level. The sample period starts from 2000 to 2020. The control variables included in the regressions are same as in Table II. All continuous variables are winsorized at 1st and 99th percentile. The regressions control fixed effects as shown in the bottom of the table. T-statistics are in parentheses. Coefficients statistically significant at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. The Logit model estimations have less observations since some facilities were dropped automatically because of all positive or all negative outcomes.

	Logit model			OLS Fixed effects
	(1)	(2)	(3)	(4)
VARIABLES	penalty_dummy	violation_dummy	enforce_dummy	ln(compliance cost)
$CPU\_high(t-1) \times ln(toxic\_release)(t-1)$	0.048**	0.062**	0.041*	0.005*
	(2.10)	(2.55)	(1.81)	(2.05)
CPU_high (t-1)	-0.192	-0.508*	-0.330	0.006
	(-0.76)	(-1.93)	(-1.36)	(0.35)
Toxic_release(t-1)	-0.028	-0.044	-0.022	-0.002
	(-0.95)	(-1.50)	(-0.78)	(-0.63)
Observations	6,318	5,949	6,393	33,900
Number of Plants	414	388	418	
Adjusted R-squared				0.017
Controls	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes
Cluster by Facility Year				Yes

Table IX: **Climate policy uncertainty and institutional ownership**

The table presents the regression results on institutional ownership. Column (1) displays the OLS regression results. Column (2) presents the first-difference regression results. Column (3) reports the Logit estimation. The dependent variables are reported at the top of each column. The independent variable of interest is lagged lnCPU. The sample period starts from 2000 to 2020. The control variables included in the regressions are same as in Table II. All continuous variables are winsorized at 1st and 99th percentile. The regressions control fixed effects as shown in the bottom of the table. Standard errors are clustered at county and year T-statistics are in parentheses. Coefficients statistically significant at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

VARIABLES	(1) InstOwn	(2) InstOwn	(3) InstOwn_low
$lnCPU(t-1) \times toxic\_high(t-1)$	-0.016*	-0.013*	0.362***
	(-2.03)	(-2.01)	(2.79)
lnCPU(t-1)	0.001	-0.021	0.220*
	(0.08)	(-1.51)	(1.80)
toxic_high(t-1)	0.060*	0.003	-1.409**
	(1.74)	(1.20)	(-2.49)
Size(t-1)	0.050***	0.017**	-0.315***
	(5.96)	(2.42)	(-4.47)
ln(firm age)(t-1)	0.096***	0.121***	-0.382*
	(2.96)	(4.04)	(-1.73)
MTB(t-1)	-0.003	0.005	-0.045
	(-0.55)	(0.93)	(-0.61)
ROA(t-1)	0.013	0.032	0.145
	(0.51)	(1.64)	(0.26)
Capex(t-1)	0.032	0.031	-1.812
	(0.24)	(0.41)	(-1.32)
R&D(t-1)	0.177	0.265**	7.252**
	(0.81)	(2.31)	(2.20)
Tangibility(t-1)	-0.187**	-0.024	0.405
	(-2.49)	(-0.92)	(0.62)
Leverage(t-1)	-0.105**	-0.047**	0.898**
	(-2.72)	(-2.28)	(2.21)
Cash Flow(t-1)	0.000	0.000	-0.000
	(0.97)	(0.88)	(-0.50)
GDP Growth(t-1)	-0.003	-0.004	0.056*
	(-0.66)	(-1.40)	(1.71)
Constant	0.110	0.005	
	(0.96)	(1.24)	
Observations	6,351	5,472	3,977
Adjusted R-squared	0.765	0.026	
Number of firms			295
Firm FE	Yes	Yes	Yes
Cluster by Firm Year	Yes	Yes	Yes

Table X: **Heterogenous effects of financial distress, CEO age and CEO tenure**

The table presents the interaction regression results. The dependent variables are toxic release and number of toxic plants. The independent variables of interest are the interaction term of lagged lnCPU and financial distress in Columns (1) and (2), the interaction term of lagged lnCPU and a dummy variable indicating whether the CEO is younger in Column (3) and (4), the interaction term of lagged lnCPU and a dummy variable indicating CEOs with short tenure in Columns (5) and (6). The sample period starts from 2000 to 2020. The control variables included in the regressions are same as in Table II. All continuous variables are winsorized at 1st and 99th percentile. The regressions control fixed effects as shown in the bottom of the table. T-statistics are in parentheses. Coefficients statistically significant at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

VARIABLES	(1) ln(toxic_release)	(2) ln(N of toxic plants)	(3) ln(toxic_release)	(4) ln(N of toxic plants)	(5) ln(toxic_release)	(6) ln(N of toxic plants)
lnCPU(t-1)	-0.651***	-0.076***	-0.437**	-0.072**	-0.501***	-0.059**
	(-4.66)	(-3.75)	(-2.68)	(-2.39)	(-3.34)	(-2.27)
Financial Distress (t-1)	-1.456*	-0.313***				
	(-2.00)	(-3.77)				
$lnCPU(t-1)\times$ $FinancialDistress(t-1)$	0.340*	0.070***				
	(2.01)	(3.73)				
CEO_young (t-1)			1.299**	-0.025		
			(2.36)	(-0.24)		
$lnCPU(t-1)\times$ $CEO\_young(t-1)$			-0.284**	0.004		
			(-2.27)	(0.17)		
CEO_short_tenure (t-1)					0.873*	0.091
					(1.96)	(1.45)
$lnCPU(t-1)\times$ $CEO\_short\_tenure(t-1)$					-0.185*	-0.022
					(-1.84)	(-1.57)
Observations	7,124	7,124	4,934	4,934	4,986	4,986
Adjusted R-squared	0.864	0.941	0.864	0.944	0.862	0.944
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Firm Year	Yes	Yes	Yes	Yes	Yes	Yes

Table XI: **Climate policy uncertainty and other outcomes**

The table presents the OLS regression results. The dependent variables are reported at the top of each column. The independent variable of interest is lagged lnCPU. The sample period starts from 2000 to 2020. The control variables included in the regressions are same as in Table II. The definitions of the variables are presented in Table AI. All continuous variables are winsorized at 1st and 99th percentile. The regressions control fixed effects as shown in the bottom of the table. T-statistics are in parentheses. Coefficients statistically significant at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

Panel A: OLS regressions

VARIABLES	(1) annual_return	(2) TQ	(3) cash	(4) ln(analysts)	(5) stock_volatility	(6) analyst_dispersion
lnCPU(t-1)	-0.260**	-0.200**	-1.312*	-0.075**	0.013***	0.033**
	(-2.35)	(-2.59)	(-1.80)	(-2.13)	(3.81)	(2.47)
Observations	6,719	7,124	7,124	6,753	6,721	5,535
Adjusted R-squared	0.184	0.771	0.674	0.872	0.610	0.205
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Firm Year	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: first-difference regressions

VARIABLES	(1) D.annual_return	(2) D.TQ	(3) D.Cash	(4) D.lnanalysts	(5) D.stock_volatility	(6) D.analyst_dispersion
D.lnCPU(t-1)	-0.480***	-0.272***	-1.717**	-0.061**	0.014***	0.038**
	(-5.86)	(-3.39)	(-2.19)	(-2.63)	(3.50)	(2.67)
Observations	6,089	6,459	6,459	6,122	6,091	4,905
Adjusted R-squared	0.503	0.077	0.115	0.036	0.285	0.007
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Firm Year	Yes	Yes	Yes	Yes	Yes	Yes

Table XII: **Climate policy uncertainty and production activities**

The table presents the OLS regression results. The dependent variable is production_ratio. The production ratio is collected by EPA data. Production_ratio captures the growth rate of the output whose production results in toxic chemical releases. The independent variable of interest is lagged lnCPU. Columns (1) and (2) report firm-level evidence. Columns (3) and (4) report facility-level evidence. The sample period starts from 2000 to 2020. The control variables are same as in Table II. All continuous variables are winsorized at 1st and 99th percentile. The regressions control fixed effects as shown in the bottom of the table. *T*-statistics are in parentheses. Coefficients statistically significant at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Firm-level	Facility-level	Facility-Chemical level
	(1)	(2)	(3)
VARIABLES	production_ratio	production_ratio	production_ratio
lnCPU (t-1)	-0.000	-0.035	-0.003
	(-0.44)	(-0.38)	(-0.63)
Size(t-1)	-0.001	0.011	-0.008
	(-1.51)	(0.81)	(-1.66)
ln(firm age)(t-1)	-0.002	-0.030	-0.006
	(-1.20)	(-0.43)	(-0.81)
MTB(t-1)	0.001**	0.020	-0.003
	(2.84)	(0.63)	(-0.86)
ROA(t-1)	0.001	0.027	-0.020
	(0.27)	(0.58)	(-0.40)
Capex(t-1)	-0.006	0.187	0.151
	(-0.55)	(0.56)	(1.03)
R&D(t-1)	-0.015	-0.693	-0.090
	(-0.68)	(-0.57)	(-1.09)
Tangibility(t-1)	-0.000	-0.553	-0.053
	(-0.02)	(-1.71)	(-1.45)
Leverage(t-1)	0.001	0.188	0.009
	(0.34)	(1.37)	(0.79)
Cash Flow(t-1)	-0.000	-0.000	0.000
	(-0.52)	(-0.98)	(0.45)
GDP Growth(t-1)	-0.000	-0.009	-0.001
	(-1.25)	(-0.40)	(-0.37)
Constant	0.027***	0.324	0.143**
	(4.40)	(1.38)	(2.87)
Observations	6,747	31,747	139,893
Adjusted R-squared	0.125	0.020	0.010
Fixed effects	Firm	Facility	Facility-Chemical
Cluster by	Firm Year	Facility Year	Facility-Chemical Year

Table XIII: **Climate policy uncertainty v.s. non-climate policy uncertainty**

The table presents the OLS regression results. The dependent variables are toxic release at the firm level, the facility-level, and the chemical-level as well as the number of toxic plants. The dependent variables are toxic release and greenhouse gas emissions. The independent variables of interest are lagged lnCPU, lnEPU. lnEPU is the natural logarithm of economic policy uncertainty index. The sample period starts from 2000 to 2020. The control variables included in the regressions are same as in Table II. All continuous variables are winsorized at 1st and 99th percentile. The regressions control fixed effects as shown in the bottom of the table. T-statistics are in parentheses. Coefficients statistically significant at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	Firm-level		Facility-level	Chemical-level	
	(1)	(2)	(3)	(4)	(5)
VARIABLES	ln(toxic_release)	ln(N of toxic plants)	ln(toxic_release)	ln(toxic_release)	ln(air)
lnCPU(t-1)	-0.531***	-0.052***	-0.431***	-0.097**	-0.103**
	(-4.30)	(-2.86)	(-4.29)	(-2.19)	(-2.55)
lnEPU(t-1)	0.038	-0.021	0.030	-0.038	-0.043
	(0.28)	(-0.90)	(0.23)	(-0.73)	(-0.90)
Observations	7,124	7,124	33,900	150,460	150,460
Adjusted R-squared	0.864	0.941	0.875	0.914	0.912
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects	Firm	Firm	Facility	Facility-Chemical	Facility-Chemical
Cluster by	Firm Year	Firm Year	Facility Year	Facility-Chemical Year	Facility-Chemical Year

Table XIV: **Controlling for climate-related policy "certainty"**

The table presents the OLS and IV regression results. The dependent variables are toxic release and number of toxic plants at the firm level. The dependent variables are toxic release and greenhouse gas emissions. The independent variables of interest are lagged lnCPU, CCAP_status. CCAP_status is a binary variable, which takes value 1 after a state has taken climate change adoption plans and 0, otherwise. The sample period starts from 2000 to 2020. The control variables included in the regressions are same as in Table II. All continuous variables are winsorized at 1st and 99th percentile. The regressions control fixed effects as shown in the bottom of the table. *T*-statistics are in parentheses. Coefficients statistically significant at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

	OLS	OLS	IV First-stage	IV Second-stage	
	(1)	(2)	(3)	(4)	(5)
VARIABLES	ln(toxic_release)	ln(N of toxic plants)	lnCPU(t-1)	ln(toxic_release)	ln(N of toxic plants)
Congress_voting(t-1)			0.064***		
			(3.71)		
lnCPU(t-1)	-0.506***	-0.048***		-0.928***	-0.085**
	(-4.08)	(-2.90)		(-4.26)	(-2.24)
CCAP_status(t-1)	-0.457**	-0.065**	-0.065	-0.406*	-0.061**
	(-2.16)	(-2.45)	(-0.78)	(-1.93)	(-2.13)
Observations	7,124	7,124	7,124	7,124	7,124
Adjusted R-squared	0.865	0.941	0.736		
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Cluster by Firm Year	Yes	Yes	Yes	Yes	Yes
Cragg-Donald Wald F-statistics				13.77	13.77

Appendix A. Derivation

In this section, I present the derivation of the trigger compliance cost for abatement investment under climate policy uncertainty (Equation 5 in the text).

The future compliance cost is denoted by τ. τ is assumed to be represented by a geometric Brownian motion with positive drift α_τ and variance rate σ_τ. Climate policy uncertainty is represented by σ_τ:

$$d\tau = \alpha_\tau \tau dt + \sigma_\tau \tau dz_\tau, \;\; where \;\; dz_\tau = \epsilon\sqrt{dt}, \;\; \epsilon \sim N(0,1). \tag{A1}$$

Denote the option value $F(\tau)$ as a function of compliance cost. ρ is the firm's discount rate, which is assumed to be exogenous. The Bellman equation is

$$\rho F(\tau)dt = E[dF(\tau)]^5. \tag{A2}$$

Applying Ito's lemma to expand $dF(\tau)$ gives

$$\frac{1}{2}\sigma_\tau^2 \tau^2 F''(\tau) + \alpha_\tau \tau F'(\tau) - \rho F(\tau) = 0. \tag{A3}$$

In addition to the above differential equation, $F(\tau)$ should satisfy the boundary conditions below:

$$F(0) = 0, \tag{A4}$$

indicating that value of option is zero when compliance cost is zero.

$$F(\tilde{\tau}) = V(\tilde{\tau}) - I, \tag{A5}$$

implying that at the trigger cost, the value of the option to invest in the abatement technology equals the net value of the investment.

$$F'(\tilde{\tau}) = V'(\tilde{\tau}), \tag{A6}$$

suggesting that at the trigger cost, the change of the option value should equal the change of the expected present value of the investment.

Given the boundary conditions, the function of $F(\tau)$ can be reduced to the form $F(\tau) = A\tau^\beta$.

The expected present value at the trigger cost is

$$V(\tilde{\tau}) = \frac{\tilde{\tau}a}{\delta} - \frac{ma}{\rho}, \; where \; \delta = \rho - \alpha_\tau. \tag{A7}$$

Equations A4 to A7 imply that

$$V(\tilde{\tau}) - I = -\frac{\tilde{\tau}a}{\delta\beta}. \tag{A8}$$

[5] The equation implies that over the interval dt, the rate of return of the option to invest should equal the expected rate of its capital appreciation.

where β is the positive square root of

$$\frac{1}{2}\sigma_\tau^2\beta(\beta-1)+\alpha_\tau\beta-\rho=0. \tag{A9}$$

Substituting A7 into A8 gives the trigger cost $\tilde{\tau}$:

$$\tilde{\tau}=\frac{\beta}{1+\beta}\,\frac{\delta}{a}\,[\frac{ma}{\rho}+I]. \tag{A10}$$

Table AI: **Variable constructions**

Variables	Definitions
ln(toxic_release)	The natural logrithm of the total pounds of toxic chemical releases aggregated at the firm, facility or chemical level.
ln(N of toxic plants)	The natural logrithm of the number of toxic emission facilities reported annually to the EPA by each firm.
production_ratio	The growth rate of the output whose production involves in toxic releases.
source_reduction	The percentage source reduction of toxic releases through an abatement technology during the production process.
penalty_dummy	A dummy variable which equals one if the facility has incur penalty at federal or state or local level in a given year and zero, otherwise.
violation_dummy	A dummy variable which equals one if the facility has at least one EPA violations in a given year and zero, otherwise.
enforcement_dummy	A dummy variable which equals one if the facility has at least one EPA enforcement in a given year and zero, otherwise.
ln(compliance cost)	The natural logrithm of the total compliance costs for each facility-year.
ln(GHG emission)	The natural logrithm of the total pounds of greenhouse gas emissions aggregated at the facility or chemical level.
ln(air)	The natural logrithm of the total pounds of toxic chemical releases to the air aggregated at the chemical level.
ln(water)	The natural logrithm of the total pounds of toxic chemical releases to the water aggregated at the chemical level.
ln(ground)	The natural logrithm of the total pounds of toxic chemical releases to the ground aggregated at the chemical level.
Size	The natural logrithm of a firm's market value of equity.
Cash flow	(IB+DP) scaled by total assets at the beginning period.
ROA	Net income scaled by total assets at the beginning period.
TQ	Market value of total assets (AT+PRCC_F*CSHO-TXDB-CEQ).
Leverage	Total debt scaled by total assets at the beginning period.
R&D	R&D expenses scaled by total assets at the beginning period.
Tangibility	Property, plant and equipment (PPENT) over total assets.
Capex	Capital expenditure (CAPX) divided by total asset.
ln(firm age)	The natural logrithm of a firm's age.
annual_return	The firm's annual stock return.
stock_volatility	The standard deviation of daily stock returns over a year.
ln(analysts)	The natural logrithm of the number of a firm's analysts following.
analyst_dispersion	The standard deviation of firms' analyst forecasts.
InstOwn	The portion of the institutional holdings of a firm.
lnCPU	The natural logrithm of averaged climate policy index in a year.
lnEPU	The natural logrithm of averaged economic policy index in a year.
GDP Growth	The growth rate of GDP.
Congress_voting	The number of congressional voting on the topics of climate change in a year.

Table AII: **Climate policy uncertainty and EPA inspections**

The table presents the logit model results on EPA inspections. The dependent variable is inspect_dummy, which is a binary variable and set to be one if the firm or facility has been inspected at least once in a given year and zero, otherwise. The independent variable of interest is a dummy variable, CPU_high, which equals to 1 if the climate policy uncertainty index of the year is above the sample median and zero, otherwise. Column (1) reports the firm-level evidence and Column (2) presents the facility-level result. The sample period starts from 2000 to 2020. The control variables included in the regressions are same as in Table II. All continuous variables are winsorized at 1st and 99th percentile. The regressions control firm fixed effects. Standard errors are clustered at county and year level. T-statistics are in parentheses. Coefficients statistically significant at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

VARIABLES	(1) inspect_dummy	(2) inspect_dummy
CPU_high (t-1)	0.300***	0.240***
	(2.66)	(2.92)
Toxic_release(t-1)	0.016	-0.015
	(0.54)	(-0.85)
Observations	4,451	12,473
Number of firms/plants	290	844
Controls	Yes	Yes
Firm FE	Yes	Yes