The Cost of Climate Policy Uncertainty: Evidence from Firm-Level Earnings Calls

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Abstract

This paper develops a firm-level index of climate policy uncertainty (CPU) using earnings call transcripts from U.S. public firms from 2002 to 2025. Using this two-decade index, firm-level panel regressions show that CPU is associated with lower employment, capital expenditures, and R&D spending. These effects are stronger among firms with greater exposure to climate policy, especially firms in more CO_2-intensive sectors. Following a 10% increase in CPU, firms with CO_2 intensity one standard deviation above the mean experience additional declines of 0.16% in employment, 0.15% in capital expenditures, and 0.67% in R&D spending relative to firms with average CO_2 intensity. CPU is also associated with lower clean patenting and green job postings, suggesting that uncertainty slows activity related to the low-carbon transition. Decomposing CPU by the tone of earnings-call discussions shows that negative CPU produces stronger and more consistent effects than positive CPU. The findings support evidence

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from news-based CPU measures and suggest that unclear or unstable climate policy can delay firm-level investment, innovation, and hiring needed for the green transition.

Keywords: climate policy uncertainty; firm investment; green innovation; earnings calls; sentiment analysis

1 Introduction

To date, 147 countries, which account for approximately 77% of global greenhouse gas emissions, have announced or are considering net-zero emissions targets (Climate Action Tracker 2025). Achieving these goals will require substantial investment in green technologies and workforce expansion in green sectors. The UNFCCC estimates that around $6 trillion will be required by 2030 to implement developing countries' climate action plans (United Nations Climate Change 2024).

Although climate policies are designed to accelerate the transition to more sustainable economies, they may also introduce uncertainty regarding future regulation, enforcement, and incentives faced by firms. New policy instruments can have ambiguous impacts on firms, and climate policies are subject to political turnover, as evident in the United States' withdrawal from the Paris Agreement. A large body of literature shows that uncertainty depresses hiring, investment, and productivity growth (Bernanke 1983).

This paper introduces a quarterly firm-level index of Climate Policy Uncertainty (CPU) based on firms' earnings calls. The index covers U.S. public firms from January 1, 2002, to December 31, 2025, providing the most recent coverage to date. Studying the effects of CPU is timely given the urgency of global warming and the need for sustained investment to address climate change. Whereas other uncertainty indices typically capture shocks viewed as broadly contractionary, CPU has the distinctive feature of generating heterogeneous effects across firms depending on their exposure to climate regulation and their position along the clean–polluting spectrum. Accordingly, this paper also introduces directional CPU, which captures whether a firm perceives CPU positively or negatively.

This paper finds firm-level evidence that higher CPU is followed by lower investment, employment, and R&D spending, with stronger effects among more polluting firms. Following a 10% increase in CPU, firms with CO_2 intensity one standard deviation above the mean reduce employment by 0.16%, capital expenditures by 0.15%, and R&D spending by 0.67%. The differential effects are weaker for the green sector outcomes, but the overall effects remain contractionary. For a firm with average CO_2 intensity, a 10% increase in CPU is associated with a 4.29% decrease in clean patenting and a 0.17% decrease in green job postings. These results are robust after controlling for Economic Policy Uncertainty and climate policy salience, and using alternative sector-level fixed effects and lag structures; appendix analyses replacing CO_2 intensity with green revenue share offers suggestive evidence from the clean end of the firm distribution.

The findings of this paper highlight the cost of an ambiguous climate policy and have important policy implications. The results indicate that CPU generates the largest declines in innovation-related outcomes, which are essential for developing and scaling sustainable technology to mitigate climate change. Making climate policies more credible and less susceptible to partisan shifts may therefore support the green transition.

1.1 Literature Review

This paper relates to many strands of literature. First, it adds to existing work that systematically quantifies uncertainty and its effects on the economy. It follows the text-based methodology introduced by Baker et al. (2016) in their article measuring Economic Policy Uncertainty (EPU)[1]. Baker et al. (2016) computes the frequency of articles in 10 leading US newspapers that contain a triple of terms: "economic" or "economy"; "uncertain" or "un-

[1] Researchers have explored various ways to measure uncertainty: text-based, survey-based, econometric-based, and market-based Cascaldi-Garcia et al. (2023). Text-based measures count the frequency of topic-related keywords in news articles or other documents; survey-based measures capture dispersion in agents' subjective forecasts; econometric-based measures define uncertainty as the conditional volatility of forecast errors Jurado et al. (2015); and market-based measures, such as the VIX, infer uncertainty from financial market volatility.

certainty"; and one or more policy-relevant terms such as "congress" or "regulation." Since Baker et al. (2016), various other indices such as Oil Price Uncertainty and Geopolitical Risk have emerged.

Second, this paper contributes specifically to the branch of literature using firm earnings call transcripts to measure uncertainty (Hassan et al. 2019; Jamilov et al. 2023; Sautner et al. 2023). These studies define the uncertainty index as the proportion of an earnings call that is devoted to the topic of interest. Hassan et al. (2019) measures political risk and finds that much of the variation in the index is firm-specific rather than aggregate or sectoral. As such, firm earnings calls capture variations that are not reflected in newspaper indices, while also providing insight into corporate perceptions.

Third, this paper contributes to the literature on CPU, pioneered by Gavriilidis (2021), who shows that CPU shocks reduce CO_2 emissions. Subsequent work examines effects of CPU on investment, employment, innovation, and stock performance (Noailly et al. 2024; Palikhe et al. 2024; Basaglia et al. 2025; Sautner et al. 2023). Noailly et al. (2024) applies text-mining machine learning to build a news-based monthly index of US environmental and climate policy and analyzes the index's correlation with Venture Capital funding for clean startups. Basaglia et al. (2025) introduces directional CPU sub-indices that distinguish uncertainty arising from policy tightening versus loosening, while Sautner et al. (2023) uses firm earnings call transcripts to measure climate exposure and study its effects on green job creation and patenting. Sautner et al. (2023) are the only authors, to this paper's knowledge, who construct firm-level indices, but they measure climate change exposure rather than uncertainty about climate policy. Other studies have expanded the scope of CPU outside of the United States (Ma et al. 2023) or examined the interplay between CPU and other uncertainty measures (Assis Attílio 2025).

This paper's index improves upon existing CPU measures in three meaningful ways. Whereas most studies construct environmental-related uncertainty measures using newspaper coverage, this paper leverages firm earnings call transcripts to directly capture managerial perceptions rather than media narratives. Bachmann et al. (2013) argue that firm-level surveys are preferable to measure the effect of uncertainty because they capture uncertainty felt by the actual decision-makers and not outside experts, such as news reporters or forecasters. Because there are no detailed surveys on firms' attitude toward environmental policies, firm earnings calls serve as a good alternative. Quarterly earnings calls are scheduled meetings where company leaders discuss performance and future outlook with financial analysts. As such, earnings calls provide relatively timely evidence on how management discuss policy-related risks.

Second, this paper constructs firm-level CPU measures, allowing for granular analysis of heterogeneity across firms and sectors. Different firms should intuitively respond differently to CPU. The main analysis uses CO_2 intensity to capture firms' exposure to transition risk, while appendix analyses use firms' shares of green revenue as an alternative measure of firms' position in the green economy. This provides a first step in addressing a key challenge in previous work, as low CO_2 intensity does not necessarily indicate a clean firm (for instance, a remote tech startup may have low emissions without any green orientation).

Third, this paper decomposes CPU into positive and negative components to examine asymmetric firm responses. Unlike prior work that defines directionality based on policy tightening versus loosening, this paper defines positive CPU as the joint presence of uncertainty and optimism expressed in transcripts, and analogously for negative CPU, thereby characterizing firms' attitude rather than the direction of the underlying policy change. This distinction is important because the same policy event may be a risk for some firms and an opportunity for other firms.

The paper proceeds as follows. Section 2 and 3 detail the construction of the CPU index and present validation checks. Section 4 describes the data sources and the construction of the green hiring and patenting measures. Section 5 outlines the empirical methodology. Section 6 presents the results and discusses their implications. Section 7 concludes.

2 Construction of CPU

This paper uses NL Analytics, a text analytics platform used in previous papers analyzing firm-level risk and uncertainty. NL Analytics primarily uses earnings call transcripts from the London Stock Exchange Group, drawing from 410,000 transcripts across 14,000 public companies and 80+ countries since 2002. This covers 80% of market capitalization in advanced economies.

NL Analytics provides the option to isolate searches to either the presentation or Q&A section of an earnings call. The entire transcript is searched through to capture CPU expressed in both prepared remarks and spontaneous analyst exchanges. Sentences from both Corporate Executives and External Participants are included, as analyst inquiries often elicit expressions of uncertainty that may not be voluntarily disclosed by management. Although NL Analytics offers the option to search adjacent sentences for keywords, co-occurrence of all terms within the same sentence is required, reducing false positives. This approach is arguably more stringent than Baker et al. (2016), who count the number of articles containing the keywords rather than requiring co-occurrence at the sentence level. Due to this restriction, the resulting index is zero for most firms and quarters.

Following the methodology of Baker et al. (2016) in building the Economic Policy Uncertainty Index, a lexicon of words for each of the three components (Climate, Policy, and Uncertainty) is created, then the frequency in which they appear in a firm-quarter earnings call is counted. Climate incorporates environment-related terms and technologies addressing climate change and global warming. Policy refers to policymaking terms and also specific climate policies. Finally, Uncertainty relies on synonyms for risk, risky, uncertain, and uncertainty from Oxford Thesaurus, excluding the words ”question,” ”questions,” and ”venture.” To avoid false positives, which are appearances that do not reflect CPU but still are captured by the search strategy, bigrams, which are more specific and less likely to have multiple meanings, are primarily used. Furthermore, to verify that chosen words are indeed used as intended, Newsbank is used to see how the words appear in the context of news articles.

To construct positive and negative subindices, sentences are additionally required to contain at least one positive or negative sentiment word, drawn from the Loughran and McDonald (2011) financial sentiment dictionary. Table 1 provides snippets of earnings call transcripts with high scoring CPU indices. These snippets are text fragments that are identified as discussing uncertainty about climate policy.

Table 1: Snippets of Top Main Climate Policy Uncertainty Exposure Firms

Firm	SIC	Time	Snippet
Black Hills Corp	4911	2008Q4	The uncertainty of potential greenhouse gas and even federal renewable portfolio standard legislation does make utility decision making difficult.
First Solar Inc	3674	2008Q4	The possibility of more expensive tax equity and its impact on solar electricity prices for both new and sending projects remains a major uncertainty going into 2009.
Butler National Corp	3721	2021Q1	Those risks include, among other things, the loss of market share through competition or otherwise, the introduction of competing technologies by other companies, new governmental safety, health and environmental regulations, which could require Butler to make significant capital expenditures.
EuroDry Ltd	4412	2025Q4	Current ordering activity remains limited due to shipyard capacity constraints, high new building costs and uncertainty surrounding future fuel technologies and environmental regulations.
Rush Enterprises Inc	5012	2025Q4	In addition, while the industry gained some clarity regarding the tariffs that will be imposed on certain commercial vehicles and parts beginning November 1, economic uncertainty and regulatory ambiguity remains, especially with respect to engine emissions regulations.

Notes: This table reports selected excerpts from firm earnings call transcripts that mentions climate policy uncertainty.

The final CPU measure is defined as the number of sentences containing all three (or four if a subindex) components divided by the total number of sentences in the earnings call that quarter for that firm (Equation 1). The resulting CPU is at the firm-quarter level, covering 7,116 public firms in the United States.

$$\mathrm{CPU}_{i,t} = \frac{\sum_{s \in \mathcal{S}_{i,t}} \mathbf{1}\left(C_s = 1 \cap P_s = 1 \cap U_s = 1\right)}{|\mathcal{S}_{i,t}|} \tag{1}$$

where $\mathcal{S}_{i,t}$ denotes the set of all sentences in the earnings call of firm i in quarter t and $|\mathcal{S}_{i,t}|$ denotes the total number of sentences in the earnings call. $C_s = 1$, $P_s = 1$, and $U_s = 1$ indicates that sentence s contains at least one term from the climate, policy, and uncertainty lexicon, respectively.

An incremental variance decomposition shows that common time effects, industry differences, and industry-by-time shocks explain only a small share of CPU variation, leaving most variation at the firm level (see Appendix C Table 10). This suggests that exposure to CPU varies substantially across firms, even firms within the same industries and time periods.

To make the index comparable to existing indices, it is aggregated across firms in two approaches. The first is a pooled measure: the count of flagged sentences across all firms is summed and divided by the total number of sentences spoken that quarter (Equation 2). This captures the fraction of all earnings call discourse devoted to CPU in a given quarter. The second is a simple average: each firm's individual index in a given quarter is summed and divided by the total number of calls that quarter. This can be interpreted as the average CPU across all firms and will not be dominated by a few extremely long transcripts. The pooled measure is plotted because it is conceptually closer to aggregate news-based CPU indices: both are the share of total text devoted to CPU, so the pooled index better captures the economy-wide salience of CPU in each quarter.

$$\mathrm{CPU}_t^{\mathrm{pooled}} = \frac{\sum_{i \in \mathcal{F}_t} \sum_{s \in \mathcal{S}_{i,t}} \mathbf{1}\left(C_s = 1 \cap P_s = 1 \cap U_s = 1\right)}{\sum_{i \in \mathcal{F}_t} |\mathcal{S}_{i,t}|} \tag{2}$$

where $\mathcal{F}_t$ denotes the set of all firms with earnings calls in quarter t, and all other notation follows the firm-level definition in Equation 1.

3 Validating the CPU Index

To improve transparency and ensure replicability, an alternative version of the index is constructed using Capital IQ, in which contents of the transcripts are directly accessible. Capital IQ provides earnings call transcripts for public and private companies globally, with coverage beginning primarily in 2008. GVKEYs of the 7,116 firms from NL Analytics are used to identify the corresponding Capital IQ transcript IDs from years 2002 to 2025. Transcript components are queried and combined into one complete transcript for each firm-quarter. Because Capital IQ provides multiple versions of earnings calls, only one version is retained, prioritizing audited final versions, followed by proofed final, edited final, and preliminary versions. The transcripts are searched through using the same Climate, Policy, and Uncertainty lexicons applied to the NL Analytics data. Sentences are identified based on the period mark while excluding common abbreviations, such as "Mr." and "i.e." Across all matched firm-call observations, the reconstructed CPU index exactly matches the NL Analytics index in 99.04% of cases. The high match rate can partially be due to the fact that most observations are zero. Among nonzero observations, agreement is lower, reflecting vendor-specific differences in transcript text, transcript versioning, and sentence segmentation.

After verifying that the CPU index is replicable and that matched snippets reflect CPU (Table 1), peaks are identified in the pooled CPU index. Peaks are defined as quarters in which the index exceeds the 90th percentile of the full sample; a peak may persist for one or more consecutive quarters.

Peaks occurred in 2002Q1, 2009Q2–2009Q4, 2010Q2–2010Q4, and 2025Q2. The 2002Q1 peak is associated with the Bush Administration's announcement of the Global Climate Change Initiative that aimed to reduce U.S. greenhouse-gas intensity by 18 percent over ten years. This event likely raised uncertainty because, while it introduced a U.S. climate strategy, it also rejected the Kyoto Protocol's emissions-cap approach and placed the United States on a different policy path from other major economies such as Japan and the European Union. The 2009Q2–2009Q4 spike is linked to the Waxman-Markey bill that proposed a nationwide cap-and-trade system for greenhouse gases. This likely increased uncertainty over future compliance costs, allowance allocation, and the distribution of regulatory burdens across firms. Uncertainty was further amplified because the bill gained substantial momentum after passing the House of Representatives but ultimately failed in the Senate, leaving the future direction of federal climate policy unresolved. The 2010Q2–2010Q4 peak is associated with the joint EPA-NHTSA National Program that paired Corporate Average Fuel Economy (CAFE) standards with greenhouse-gas tailpipe standards. The program required automakers to produce vehicles that were both more fuel-efficient and less carbon-intensive, with potential implications extending beyond automakers to suppliers and energy producers. Finally, 2025Q2, under the Trump administration, saw the reversal of many Biden administration climate policies that raised questions about the durability of prior regulations and the future direction of U.S. climate policy. For example, the April 8, 2025 executive order targeted state-led climate policies relevant to climate change, carbon taxes, and ESG. Furthermore, on June 11, 2025, the EPA proposed to repeal all greenhouse gas emissions standards for fossil-fuel power plants.

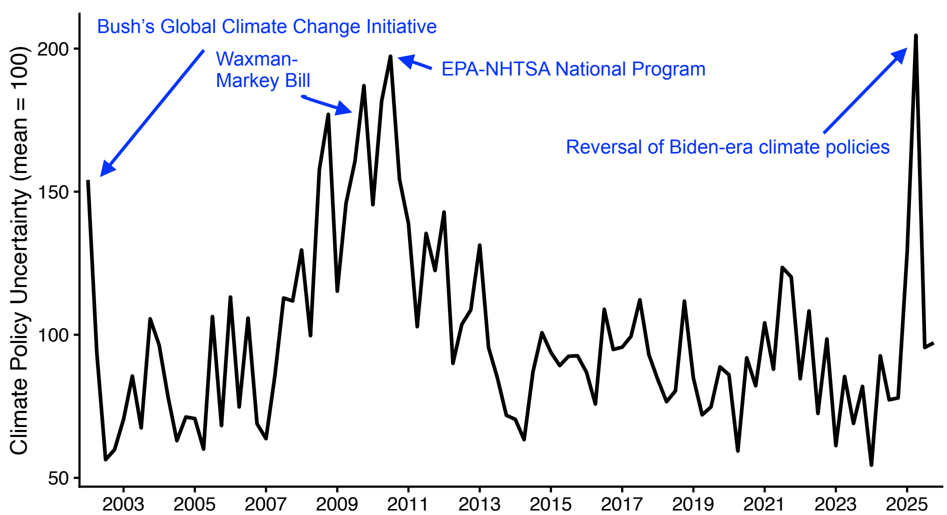

Figure 1: Aggregate pooled CPU index normalized to mean 100 and climate policy events

As opposed to aggregated news-based indices, this pooled average is constructed from earnings calls. As such, spikes in the index should be more closely tied to events that matter to firms rather than to the general public. For example, it may be more sensitive to implementation-type events that alter firms' expected compliance costs, regulatory obligations, or investment incentives, rather than to politically salient or symbolic events. As an example, Basaglia et al. (2025) identified the 2017 U.S. withdrawal from the Paris Agreement as a key episode, but this event does not generate a spike in this paper's index, likely because the Paris Agreement was an international treaty whose immediate firm-level implications were less direct than those of domestic regulatory or legislative changes.

3.1 Negative and Positive CPU

The main CPU measure is supplemented with positive and negative CPU subindices. Although directional components are sparse in text-based uncertainty measures, the broader uncertainty literature has decomposed uncertainty. For example, Segal et al. (2015) define good uncertainty as volatility associated with positive macroeconomic shocks, and bad uncertainty analogously, and show that the two have opposite effects on growth and asset prices. Dahlhaus and Sekhposyan (2018) decompose monetary policy uncertainty into downside uncertainty—when the policy rate may be higher than expected—and upside uncertainty—when the policy rate may be lower than expected. They find that the recessionary effects of a monetary easing regime are stronger. Finally, Basaglia et al. (2025), whose framework is closest to this paper's, define positive CPU as expectations of more climate policy action and negative CPU as expectations of less climate policy action.

The positive CPU is constructed by requiring a sentence in an earnings call to contain, in addition to the climate, policy, and uncertainty terms, at least one positive word, such as "excited," "progress," or "favorable." Similarly, the negative CPU is constructed by requiring the sentence to contain at least one negative word, such as "bad," "challenging," or "depress." The full lists of positive and negative words are reported in Appendix A. By construction, however, this paper's measure differs from Basaglia et al. (2025): positive CPU captures the firm's own tone toward the climate-policy discussion rather than the direction of policy itself. As a result, a positive tone does not necessarily imply that the policy is expansionary or favorable to clean firms, just as a negative tone does not necessarily imply policy loosening or unfavorable effects on polluting firms. Appendix Section B includes snippets of top scoring CPU subindices. Plotting the positive and negative CPU indices, the negative CPU more closely follows the main CPU (Figures 2 and 3).

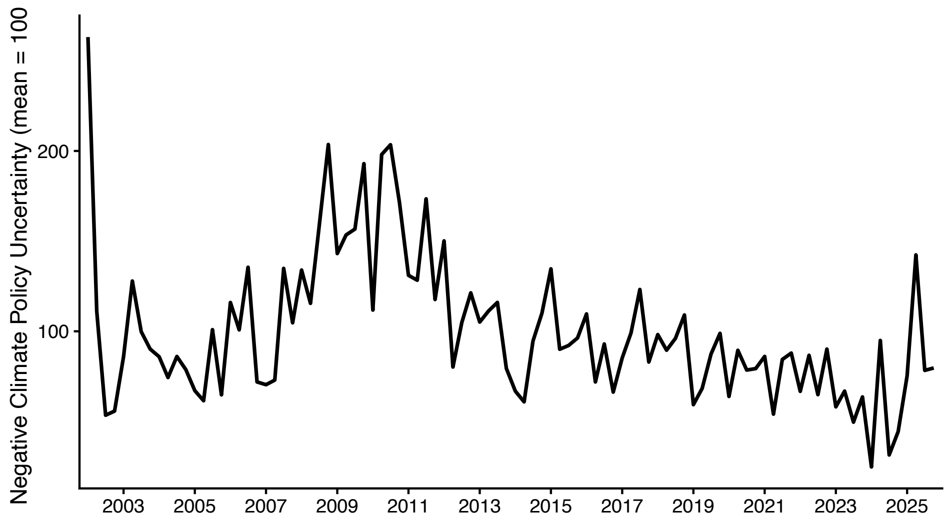

Figure 2: Aggregate negative pooled CPU index normalized to mean 100

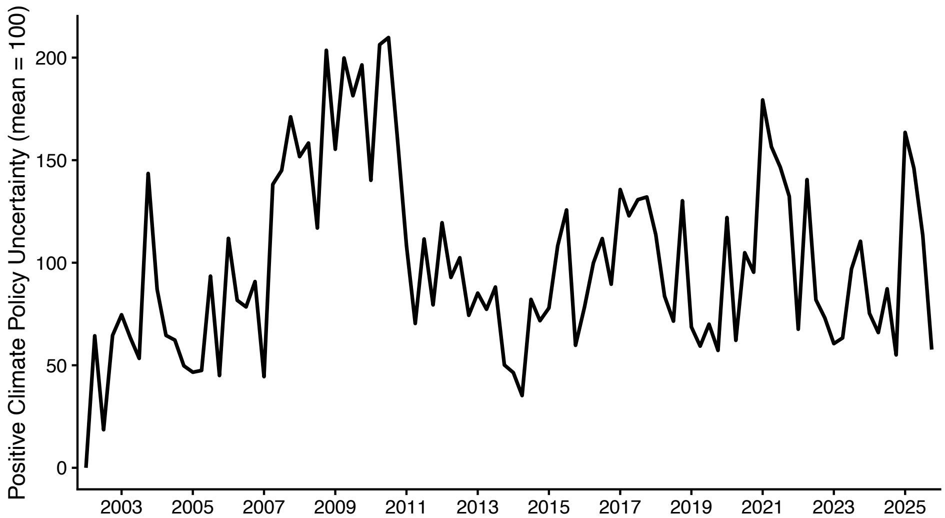

Figure 3: Aggregate positive pooled CPU index normalized to mean 100

3.2 Comparing CPU to Existing Indices

Because Gavriilidis (2021); Palikhe et al. (2024); Noailly et al. (2024); Basaglia et al. (2025) develop conceptually similar measures—namely, indices capturing uncertainty related to climate or environmental policies—the correlations between their index and this paper's index is computed. However, three differences should be noted. First, these indices differ in scope: some focus specifically on climate policy, while others address environmental policy more broadly. Environmental policy encompasses a wider range of issues, such as biodiversity protection, whereas climate policy is primarily concerned with climate change and global warming. Second, the methodologies employed across these studies vary, particularly in their search strategies and the construction of keyword lexicons. Third, all of these papers rely on newspaper articles, whereas this paper's measure is derived from firm earnings call transcripts. In order to allow for comparability, the pooled and firm-average CPU indices described above are used.

Gavriilidis (2021), as a pioneering contribution, employs a relatively simple lexicon that later studies expand upon. Palikhe et al. (2024) restrict their sample to articles related to economic policy uncertainty that also contain at least one of 31 environmental keywords. Compared to Palikhe et al. (2024), this paper's search does not require call transcripts to be about economic policy uncertainty. Noailly et al. (2024) apply text-mining techniques to identify relevant articles and construct a combined climate and environmental policy uncertainty index. Finally, Basaglia et al. (2025) develop a CPU index with a particular emphasis on minimizing false positives. Gavriilidis (2021); Palikhe et al. (2024); Basaglia et al. (2025) follow the keyword-based search approach introduced by Baker et al. (2016).

Because this paper's index is closest in concept and search strategy to Basaglia et al. (2025), it has a 0.67 correlation coefficient for both pooled and firm-average. The pooled measure has a correlation coefficient of 0.41 with Gavriilidis (2021), 0.37 with Palikhe et al. (2024), and finally 0.08 with Noailly et al. (2024) as shown in Figure 4. The moderate correlations suggest that earnings-call CPU captures firm-perceived uncertainty rather than reflecting media salience.

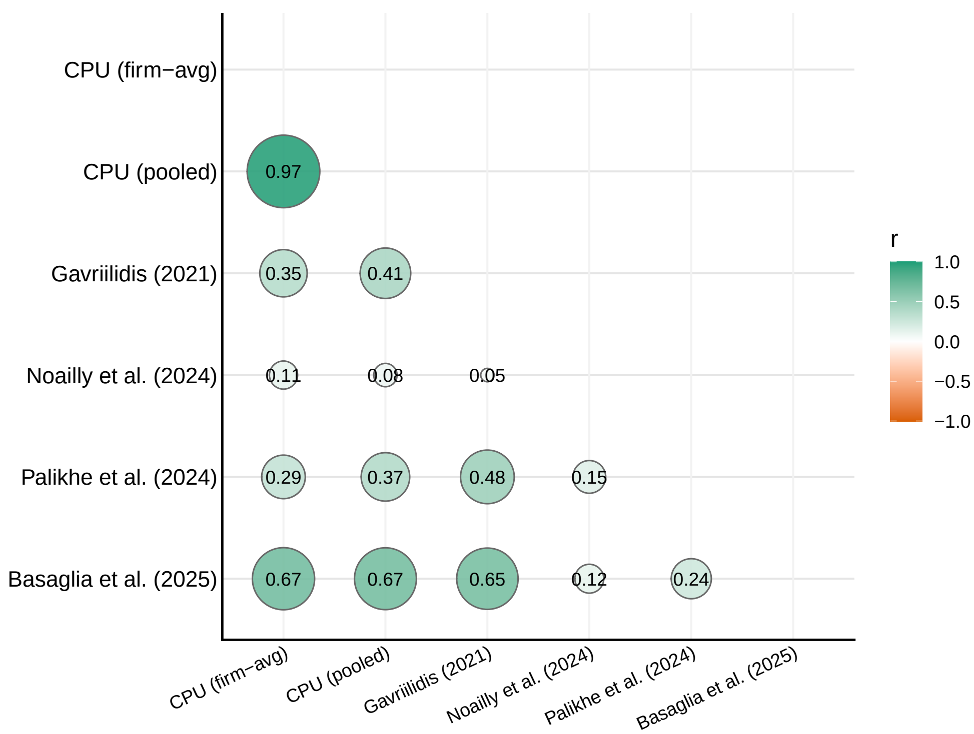

Figure 4: Comparing Aggregate CPU (pooled and firm-avg) with other indices

4 Data

4.1 Firm outcome variables

To examine the effects of CPU on firm-level outcomes, data on firm hiring, investment, and innovation are collected. Compustat North America, which compiles firm information from 10-K filings, provides annual data on employment, research and development (R&D), and capital expenditure (CAPEX). CAPEX is used as a proxy for investment, as it captures how much a firm spends on acquiring, upgrading, or maintaining long-term physical assets such as property, plants, and equipment.

To supplement Compustat's R&D data, firm-level patent data is additionally obtained as a second proxy for innovation. Patent data present several advantages over other measures of innovation: first, they are standardized, as patentable inventions must be novel, non-obvious, and useful; second, unlike R&D expenditures, which measure inputs, patents capture intermediate output, indicating that a firm's spending on innovation produced a concrete result; and third, patents can be decomposed by specific technological fields, such as environmental technologies for the purposes of this paper (Haščič and Migotto 2015). Two patent data sources are combined to expand coverage: WRDS US Patents and PatentsView. The current version of WRDS US Patents covers only the years 2011 to 2020, while PatentsView spans 2001 to 2025. Both databases parse USPTO XML files. PatentsView transforms the raw data into structured tables with consistent identifiers for inventors, assignees, and locations.

Because this paper is interested in CPU's effects on green patenting specifically, rather than total patenting, the Environment-related technologies (ENVTECH) search strategy of Haščič and Migotto (2015) is applied to identify environmental technologies. The ENVTECH classification covers approximately 80 technological fields organized under 4 broad environmental objectives: environmental health, water scarcity, ecosystem health and biodiversity, and climate change. Haščič and Migotto (2015) map specific International Patent Classification (IPC) and Cooperative Patent Classification (CPC) codes to each environmental technology category. While CPC is newer and more granular, IPC is older and aligns more closely with established green inventories.

To supplement Compustat's employment data, the Revelio Labs COSMOS job posting dataset is obtained. Because interest is in how green hiring responds to CPU, a continuous measure of each occupation's green intensity is constructed. The O*NET-SOC system is the primary federal database of occupational information in the United States. The O*NET Green Task file, which classifies tasks as green or non-green for 138 occupations that underwent green task development, is used. For each occupation, the share of green tasks is computed. Each occupation is identified by an SOC code, which is used to link O*NET occupations to job postings in COSMOS. For each job posting in COSMOS, the following are assigned: (i) a measure of its greenness based on the share of green tasks and (ii) its share of the firm's total job postings in that quarter. Green job postings are computed by summing the greenness of all job postings within a firm-quarter, which can be interpreted as the effective number of green jobs posted. Total job postings is just the number of postings per firm-quarter.

4.2 Controls

To control for firm size, financial performance, and other firm characteristics, annual and quarterly firm-level data from Compustat are obtained, including total assets, debt, cash holdings, property, plant, and equipment (PPE), earnings before interest and taxes (EBIT), capital expenditures (CAPEX), and research and development (R&D) expenditures. Using these variables, the following firm characteristics are computed: firm size (log assets), leverage (debt-to-assets), asset tangibility (PPE-to-assets), cash holdings (cash-to-assets), profitability (EBIT-to-assets), investment intensity (CAPEX-to-assets), and innovation intensity (R&D-to-assets). Additionally, CPU may capture broader discussions of climate policy rather than purely uncertainty. To separate these channels, climate policy salience is controlled for. Climate policy salience is defined as the share of sentences in an earnings call that contain terms in the climate and policy lexicons, but do not contain terms in the uncertainty lexicon.

4.3 Emission intensity

Polluting firms are expected to respond differently to CPU than clean firms. Following the methodology of Basaglia et al. (2025), firms' exposure to environmental policy is proxied by sector-level emission intensity, measured as kg CO_2 emissions per \$1 sector output, from the US Environmentally-Extended Input-Output (USEEIO) database. The most recent version of the USEEIO database covers 389 industry sectors and reports Scope 1 emissions for the year 2013. The USEEIO models combine economic input-output tables from the Bureau of Economic Analysis with environmental data on resource use and pollutant releases from various public sources, tracing how economic activity across industries translates into environmental impact. As such, emission intensity is a model-based estimate rather than a direct measurement. In the regressions, emission intensity is aggregated to the NAICS-4 level, as more granular levels yield sparse data. Emission intensity is held constant over time to avoid reverse causality. The NAICS-4 sectors with the highest CO_2 intensity are reported below in Figure 5 and Table 2. As shown, Electric Power Generation ranks highest at 6.193 kg CO_2e/\$, followed by Lime and Gypsum Product Manufacturing at 3.16 kg CO_2e/\$.

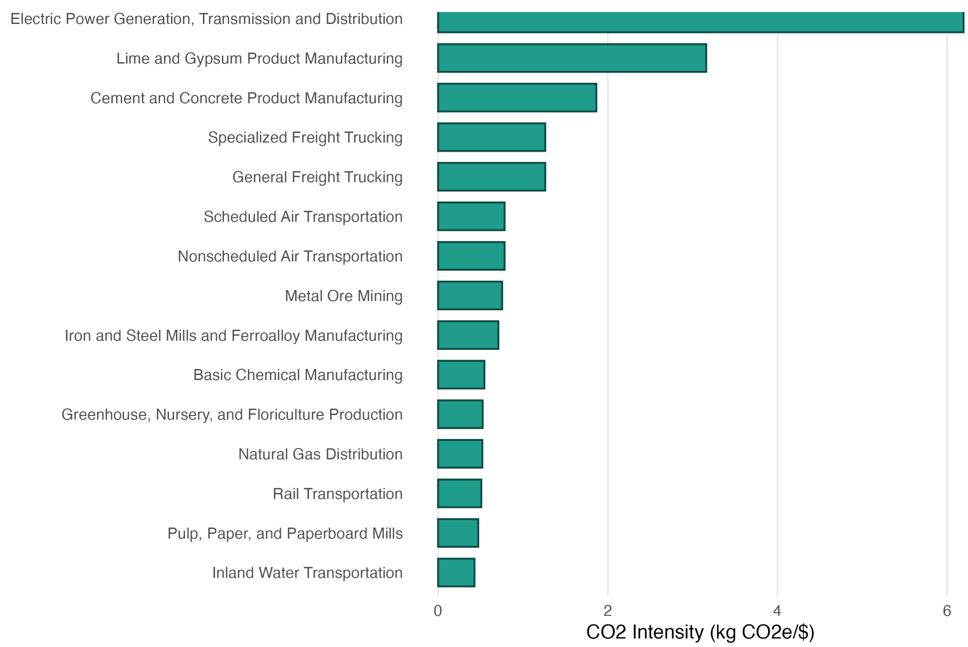

Figure 5: Top 15 Polluting Sectors by CO_2 Intensity

Table 2: Top CO_2 Intensive NAICS-4 Sectors

NAICS-4	Sector	CO_2 Intensity
2211	Electric Power Generation, Transmission and Distribution	6.1934
3274	Lime and Gypsum Product Manufacturing	3.1605
3273	Cement and Concrete Product Manufacturing	1.8651
4842	Specialized Freight Trucking	1.2629
4841	General Freight Trucking	1.2629
4811	Scheduled Air Transportation	0.7841
4812	Nonscheduled Air Transportation	0.7841
2122	Metal Ore Mining	0.7552
3311	Iron and Steel Mills and Ferroalloy Manufacturing	0.7105
3251	Basic Chemical Manufacturing	0.5457
1114	Greenhouse, Nursery, and Floriculture Production	0.5255
2212	Natural Gas Distribution	0.5211
4821	Rail Transportation	0.5093
3221	Pulp, Paper, and Paperboard Mills	0.4732
4832	Inland Water Transportation	0.4287

Notes: CO_2 intensity is from USEEIO database and measured as kilogram of CO_2 emissions per $1 sector output.

4.4 Share of green revenue

Each firm's share of green revenue is used as a proxy for its environmental orientation. Compared to other proxies such as the "E" in ESG ratings or Scope 1 emissions that are more operations-oriented, green revenues reflect a firm's ability to generate profit from sustainable activities (Klaumann et al. 2024). Green revenue shares are sourced from London Stock Exchange Group's Green Revenues Data Model, which covers more than 21,000 listed companies across 49 developed and emerging markets. LSEG calculates green revenue shares using two approaches. First, the company engages directly with LSEG to report its green revenue breakdown ("disclosed"). Second, when a company provides limited revenue disclosures, LSEG analysts estimate green revenue using other information such as production volume or peer data ("company-specific"). LSEG further specifies a tiered classification: Tier 1 denotes activities with significant environmental benefits, Tier 2 denotes activities with limited environmental benefits, and Tier 3 denotes activities that are approximately net neutral or even net negative. For cleaner identification, only revenue that is derived from Tier 1 activity was taken into account. Tier 1 green revenue percentages for each firm are collected over the past 10 years. As noted in Klaumann et al. (2024), LSEG only provides point estimates from 2016 onward, while earlier observations offer upper and lower bounds. Similar to emission intensity, green revenue is treated as time-invariant to avoid reverse causality: for each firm, the earliest available point estimate (post 2016) is taken and held constant throughout the regression period.

4.5 Correlation between CPU and moderators

Polluting and sustainable firms are expected to face greater CPU, as both are exposed to climate-related policy changes. Following Sautner et al. (2023), two cross-sectional regressions of standardized long-run CPU are estimated: one on standardized time-invariant CO_2 intensity and one on standardized green revenue share. Because CO_2 intensity is measured at the NAICS-4 level and is time-invariant, NAICS-2 fixed effects are used to absorb broad industry heterogeneity while preserving within-NAICS-2 variation in CO_2 intensity. Standard errors are clustered at the NAICS-4 sector level to allow for correlated residuals within the level at which the CO_2 variable varies. Long-run CPU is defined as each firm's average CPU value over time. The coefficient on green revenue share is positive and statistically significant, while the coefficient on CO_2 intensity is positive but not statistically significant (Table 3).

Table 3: CPU correlation with CO_2 Int and Green Revenue Share

	(1) CPU	(2) CPU
Green revenue share	0.060***	
	(0.021)	
CO_2 int		0.117
		(0.084)
Industry FE	NAICS2	NAICS2
Firms	1,775	3,468

Notes: This table reports coefficients from regressions of standardized long-run CPU on standardized green revenue share and standardized CO_2 intensity, respectively. Standard errors are clustered at the NAICS-4 level, and all specifications include NAICS-2 fixed effects. Long-run CPU is defined as the firm-level average of CPU over the sample period.

5 Methodology

5.1 CPU Aggregation and Data Preparation

Because real outcomes and patent outcomes are annual, annual firm-level CPU measures are constructed. For each firm-year, the mean of the firm's call-level CPU observations is taken (separately for the main, positive, and negative CPU series). Each series is then normalized to have sample mean 100 and logged, following the Baker, Bloom, Davis (2016) convention.

The moderator variables are prepared as follows: sectoral CO_2 intensity is standardized (z-score), while green revenue is used as a continuous firm-level share. The control vector includes lagged firm characteristics: firm size (log assets), leverage (debt-to-assets), asset tangibility (PPE-to-assets), cash holdings (cash-to-assets), profitability (EBIT-to-assets), investment intensity (CAPEX-to-assets), and innovation intensity (R&D-to-assets). As a robustness check, lagged EPU interacted with SIC-derived firm-level government contract exposure is included to separate CPU effects from broader economic policy uncertainty. Firm employment, R&D, and CAPEX are logged. Patent data are winsorized at the 1st and 99th percentiles.

For notational simplicity, logged variables are written as $\log(x)$ throughout the equations and tables, but all logarithmic transformations are implemented as $\log(1+x)$ to account for zero values.

5.2 Baseline Real Outcomes Model

To estimate how firm employment, R&D, and CAPEX respond to CPU, the following specification is estimated:

$$y_{it} = \alpha + \beta_1 \, \mathrm{CPU}^{(s)}_{i,t-1} + \beta_2 \Big(\mathrm{CPU}^{(s)}_{i,t-1} \times M_i \Big) + M_i + \theta \, \mathrm{CPS}_{i,t-1} + \mathbf{X}_{i,t-1} + \gamma_{\mathrm{naics4}(i)} + \delta_t + \varepsilon_{it}, \quad (3)$$

where y_{it} is the outcome for firm i in year t (log(1+Emp), log(1+R&D), or log(1+CAPEX)). $\mathrm{CPU}^{(s)}_{i,t-1}$ is the transformed lag-1 CPU measure with $s \in \{\mathrm{main}, \mathrm{pos}, \mathrm{neg}\}$, and M_i is either time invariant CO_2 intensity or green revenue share. $\mathrm{CPS}_{i,t-1}$ denotes lagged climate policy salience, defined as the share of earnings call sentences discussing climate policy. $\mathbf{X}_{i,t-1}$ is the vector of lag-1 firm controls, $\gamma_{\mathrm{naics4}(i)}$ are NAICS-4 fixed effects, δ_t are year fixed effects, and ε_{it} is the error term (with standard errors clustered at the firm level). When R&D is the dependent variable, R&D-to-assets is excluded from controls; when CAPEX is the dependent variable, CAPEX-to-assets is excluded, to avoid mechanical overlap. β_1 and β_2 are the coefficients of interest.

The NAICS-4 fixed effects absorb permanent differences across narrowly defined industries, while the year fixed effects absorb aggregate shocks common to all firms in a given year. β_2 captures whether the firm-level effect of CPU on outcomes differs by the level of

M_i. When M_i is green revenue share, both terms in the interaction vary at the firm level, so β_2 is identified from within-NAICS-4 differences across firms. When M_i is CO_2 intensity, it is defined at the NAICS-4 level and is absorbed by $\gamma_{\text{naics4}(i)}$ in isolation. However, its interaction with firm-level $\text{CPU}^{(s)}_{i,t-1}$ remains identified, as firms within the same NAICS-4 still differ in their CPU exposure.

5.3 Patent PPML Model

Because patent outcomes are nonnegative, highly skewed, and include many zeros, Poisson pseudo-maximum-likelihood (PPML) estimation is used, as it provides consistent estimates for dependent variables with these characteristics. The estimating equation is:

$$y_{it} = \exp\Big(\alpha + \beta_1\,\text{CPU}^{(s)}_{it,\text{sum12}} + \beta_2\,\text{CPU}^{(s)}_{it,\text{sum12}} \times M_i + M_i + \theta\,\text{CPS}_{i,t-2} + \mathbf{X}_{i,t-2} + \gamma_{\text{naics2}(i)} + \delta_t + \varepsilon_{it}\Big), \tag{4}$$

where y_{it} is either total or clean patent outcome for firm i in year t. The main regressor is $\text{CPU}^{(s)}_{it,\text{sum12}}$, defined as a cumulative lagged measure based on information available up to $t-1$:

$$\text{CPU}^{(s)}_{it,\text{sum12}} = \log\Big(1+\text{CPU}^{(s)}_{i,t-1}\Big) + \log\Big(1+\text{CPU}^{(s)}_{i,t-2}\Big)\,, \tag{5}$$

with $s \in \{\text{main}, \text{pos}, \text{neg}\}$. $\text{CPS}_{i,t-2}$ denotes lagged climate policy salience, M_i denotes the time-invariant moderator (CO_2 intensity or green revenue share), while $\mathbf{X}_{i,t-2}$ is the vector of lag-2 firm controls. $\gamma_{\text{naics2}(i)}$ and δ_t denote NAICS-2 industry and year fixed effects, respectively.

An additional advantage of PPML is that it accommodates separable group (industry and year) fixed effects by relying on within-group variation among observations with at least one positive outcome (Cohn et al. 2022). Consequently, identification is driven by firm-year observations with nonzero patenting activity.

Because patenting activity is sparse and unevenly distributed across narrowly defined industries, NAICS-2 fixed effects are used to ensure sufficient within-cell variation while still controlling for broad sectoral differences in innovation. Consistent with delayed innovation response, a distributed-lag style specification is estimated to capture cumulative two-year effects (t-1, t-2). Robustness specifications adding lagged EPU interacted with SIC-derived firm-level government contract exposure is reported as well.

5.4 Job Postings PPML Model

Similar to patent outcomes, job postings are also nonnegative, highly skewed, and contain a large mass of zeros. The model is therefore estimated using PPML, with NAICS-4 and quarter fixed effects and the same control variables. Because hiring adjusts more quickly than patenting activity, the specification focuses on the one-period lag of CPU. The estimating equation is otherwise identical to the patent specification:

$$y_{it} = \exp\Big(\alpha + \beta_1 \,\mathrm{CPU}^{(s)}_{i,t-1} + \beta_2 \,\mathrm{CPU}^{(s)}_{i,t-1} \times M_i + M_i + \theta \,\mathrm{CPS}_{i,t-1} + \mathbf{X}_{i,t-1} + \gamma_{\mathrm{naics4}(i)} + \delta_t + \varepsilon_{it}\Big), \quad (6)$$

where y_{it} is either total or green job postings for firm i in quarter t. The main regressor is $\mathrm{CPU}^{(s)}_{i,t-1}$, with $s \in \{\mathrm{main}, \mathrm{pos}, \mathrm{neg}\}$. $\mathrm{CPS}_{i,t-1}$ denotes lagged climate policy salience, M_i denotes the time-invariant moderator (CO_2 intensity or green revenue share), while $\mathbf{X}_{i,t-1}$ is the vector of lag-1 firm controls. $\gamma_{\mathrm{naics4}(i)}$ and δ_t denote NAICS-4 industry and quarter fixed effects, respectively.

This empirical strategy does not fully eliminate endogeneity concerns, as unobserved firm or sector specific shocks may affect both CPU discussions and firm outcomes. The estimates should therefore do not necessarily identify causal effects, but they remain informative because they test whether firm-perceived CPU predicts subsequent changes in real activity, especially among firms more exposed to climate policy.

6 Results

The empirical results highlight three main findings. First, CPU is associated with lower real activity among more emissions-intensive firms, with the strongest evidence for employment, capital expenditures, and R&D. Second, CPU is associated with lower patenting, suggesting that uncertainty also affects innovation, including green innovation, although the patent results provide weaker evidence of differential effects by CO_2 intensity. Third, CPU is associated with lower total and green job postings, though heterogeneity patterns are not prominent. Therefore, firm activity results provide the strongest evidence for heterogeneous real effects, while patent and hiring results provide complementary evidence on innovation and labor adjustment.

6.1 Real Outcomes

Table 4 reports how real outcomes respond to main CPU and negative CPU. The direct effect of main CPU is negative across employment, R&D, and CAPEX, but only significant for R&D. The key result is the interaction: the CPU effect becomes more negative in more carbon-intensive sectors.

Results using negative CPU are qualitatively similar but stronger in magnitude and significance, indicating that real outcomes are driven more by "bad" CPU shocks. By contrast, positive CPU delivers weaker and less consistent interaction effects, with limited statistical significance. Results for positive CPU are reported in Appendix F.

The findings are robust to additional controls, including EPU $\times$ intensity of firm-level exposure to government purchases and alternative fixed effects specifications. In particular, re-estimating the model with NAICS-2 fixed effects yields similar results, while allowing for more variation in sector-level variables such as CO_2 intensity, which is defined at the NAICS-4 level. These robustness checks are reported in Appendix E.

Because CO_2 intensity is standardized, the interaction coefficient β_2 captures how the

Table 4: Outcome OLS: Main and Negative CPU

	(1) log(Emp)	(2) log(R&D)	(3) log(CAPEX)
Panel A: Main CPU			
$\log(\text{CPU})_{t-1}$	-0.006	-0.017	0.0003
	(0.005)	(0.012)	(0.006)
$\log(\text{CPU})_{t-1} \times \text{CO}_2$ int	-0.017^{***}	-0.071^{***}	-0.016^{*}
	(0.006)	(0.015)	(0.009)
Panel B: Negative CPU			
$\log(\text{CPU}^{-})_{t-1}$	-0.005	-0.023	-0.003
	(0.005)	(0.015)	(0.005)
$\log(\text{CPU}^{-})_{t-1} \times \text{CO}_2$ int	-0.018^{***}	-0.075^{***}	-0.017^{***}
	(0.005)	(0.013)	(0.006)
Observations	24,778	25,046	25,061
Firms	3,064	3,076	3,082
NAICS-4 FE	yes	yes	yes
Year FE	yes	yes	yes

Notes: This table reports estimates from Equation 3. Standard errors clustered at the firm level are reported in parentheses. The significance level is denoted as * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). Dependent variables are drawn from Compustat North America. Panel A uses main CPU, measured as the frequency of sentences referencing climate policy uncertainty in firm-quarter earnings calls; Panel B uses negative CPU, measured as the frequency of sentences referencing climate policy uncertainty in a negative tone. Both measures are aggregated to the annual level, normalized to have mean 100, and log-transformed. CO_2 intensity is sourced from the USEEIO database and is defined at the NAICS-4 level. Controls include Compustat firm characteristics and climate policy salience. All specifications include NAICS-4 and year fixed effects. All logged variables are defined as $\log(1 + x)$. The sample consists of firm-year observations with non-missing values for all dependent and independent variables.

effect of CPU differs for a one-standard-deviation higher value of CO_2 intensity. Under a counterfactual 10% increase of $(1 + \mathrm{CPU}^{(s)}_{i,t-1})$, the interaction term implies an additional percent change in the outcome of

$$\left(1.1^{\beta_2} - 1\right) \times 100.$$

Calculation details are provided in Appendix D.1. Using the estimates in Panel A of Table 4, a one-standard-deviation higher CO_2 intensity is associated with an additional effect of approximately 0.16% decrease for employment, 0.67% decrease for R&D, and 0.15% decrease for CAPEX in response to a 10% increase in $(1 + \mathrm{CPU})$. In the negative CPU specification, the corresponding differential effects relative to average CO_2 intensity are 0.17% drop in employment, 0.71% drop in R&D, and 0.16% drop in CAPEX.

To assess the economic significance, the percentage effects are translated to level effects. Using the regression sample in Panel A of Table 4, the average firm has 11,700 employees, \$234.4 million in annual R&D spending, and \$246.0 million in annual capital expenditures. With respect to these baseline values, a 10% increase in CPU implies an additional decline of approximately 18 employees, \$1.6 million in R&D spending, and \$0.4 million in capital expenditures for a firm one standard deviation higher in CO_2 intensity.

While these numbers may seem small, R&D has social returns that exceed private returns. Jones and Williams (1998) finds that efficient R&D investment can be more than two to four times actual investment. Therefore, even modest reductions in R&D can have spillovers beyond the firm. Furthermore, employment losses can have worker-level consequences even if the firm does not internalize them. Jacobson et al. (1993) finds that long-term earnings losses average to about 25% annually for displaced high-tenure workers. More recent evidence suggests that displaced workers experience long-run earnings losses of 22%, about one-quarter of which is due to the loss of favorable firm pay premiums (Moore and Scott-Clayton 2025). These firm-specific wage losses are especially large for workers displaced from manufacturing firms, which account for several of the top polluting sectors in Figure 5; among these workers, lost firm rents explain about half of earnings losses.

Furthermore, Table 5 shows the effect of a 10% increase in main CPU for NAICS-4 sectors using sector-specific CO_2 intensity. The reported sectors correspond to the most carbon-intensive industries in Table 2.

Table 5: Sectoral Effects of Main CPU

NAICS-4	Sector	CO_2 (z)	Emp	R&D	CAPEX
2211	Electric Power Generation, Transmission and Distribution	10.9390	-1.76%	-7.24%	-1.62%
3274	Lime and Gypsum Product Manufacturing	5.4463	-0.91%	-3.75%	-0.81%
3273	Cement and Concrete Product Manufacturing	3.1003	-0.54%	-2.22%	-0.46%
4841	General Freight Trucking	2.0098	-0.37%	-1.50%	-0.30%
4842	Specialized Freight Trucking	2.0098	-0.37%	-1.50%	-0.30%
4811	Scheduled Air Transportation	1.1426	-0.23%	-0.93%	-0.17%
4812	Nonscheduled Air Transportation	1.1426	-0.23%	-0.93%	-0.17%
2122	Metal Ore Mining	1.0902	-0.23%	-0.89%	-0.16%
3311	Iron and Steel Mills and Ferroalloy Manufacturing	1.0093	-0.21%	-0.84%	-0.15%
3251	Basic Chemical Manufacturing	0.7110	-0.17%	-0.64%	-0.10%
1114	Greenhouse, Nursery, and Floriculture Production	0.6744	-0.16%	-0.61%	-0.10%
2212	Natural Gas Distribution	0.6663	-0.16%	-0.61%	-0.10%
4821	Rail Transportation	0.6450	-0.15%	-0.59%	-0.09%
3221	Pulp, Paper, and Paperboard Mills	0.5796	-0.14%	-0.55%	-0.08%
4832	Inland Water Transportation	0.4991	-0.13%	-0.50%	-0.07%

Notes: This table reports the sample of firms in top polluting NAICS-4 sectors. CO_2 intensity is sourced from USEEIO database. The effects of a 10% increase in main CPU are calculated using coefficients in Panel A of Table 4.

Specifically, the implied percent change in outcomes is given by

$$\left(1.1^{\beta_1+\beta_2 M_s} - 1\right) \times 100,$$

where β_1 is the coefficient on main CPU and β_2 is the coefficient on the interaction term from Panel A of Table 4, and M_s denotes the standardized CO_2 intensity of sector s.

6.2 Patenting

The patent results show a robust negative relationship between CPU and subsequent innovation (Table 6). However, unlike the real outcome regressions, this effect is driven primarily by the direct CPU coefficient rather than by the interaction with CO_2 intensity. These results suggest that CPU depresses innovation broadly, rather than that patenting response is concentrated among high-emissions firms.

This difference between the R&D and patenting results is consistent with the fact that the two outcomes capture different stages of the innovation process, as discussed in Section 4. R&D is an input that may adjust relatively quickly to changes in CPU, whereas patents are a noisier output measure that capture only a subset of underlying innovative activity (Griliches 1990). Patent outcomes depend on a broader set of factors, including firm-specific innovation capacity, technological opportunities, and longer planning horizons that may attenuate differential responses across firms. Thus, CO_2 intensity appears to more strongly shape near-term operating and investment responses than number of patents.

Using the PPML estimates, the implied effect of a 10% increase in each lagged $(1+\text{CPU})$ term is given by

$$\left(1.21^{\beta_1+\beta_2 M_i} - 1\right) \times 100,$$

reflecting the cumulative lag structure (see Appendix D.2). For a firm with average CO_2 intensity ($M_i = 0$), this corresponds to an expected decline of approximately 2.37% in total patents and between 4.18% and 4.29% in clean patents. Under the negative CPU specification, the expected decline is about the same, with 2.24% in total patents and between 4.03% and 4.09% in clean patents. In the regression sample in Panel A of Table 6, firms average 72 total patents and 4.8 clean patents per year. Applying the estimated percentage effects to these baselines implies a decline of approximately 2 total patents and 0.2 clean patents per firm-year.

For a firm with CO_2 intensity one standard deviation above the mean ($M_i = 1$), the

Table 6: Patenting: Main and Negative CPU

	(1) Total patent	(2) Clean patent	(3) Clean patent
Panel A: Main CPU			
$\log(\text{CPU})_{t-1,t-2}$	-0.126^{***}	-0.230^{***}	-0.224^{***}
	(0.047)	(0.075)	(0.076)
$\log(\text{CPU})_{t-1,t-2} \times \text{CO}_2$ int	0.135	-0.052	-0.119
	(0.121)	(0.230)	(0.180)
Panel B: Negative CPU			
$\log(\text{CPU}^{-})_{t-1,t-2}$	-0.119^{***}	-0.216^{***}	-0.219^{**}
	(0.040)	(0.074)	(0.093)
$\log(\text{CPU}^{-})_{t-1,t-2} \times \text{CO}_2$ int	0.132	-0.117	-0.097
	(0.139)	(0.182)	(0.155)
Observations	883	881	868
Firms	113	112	109
NAICS-2 FE	yes	yes	yes
Year FE	yes	yes	yes
EPU $\times$ Gov purchase int	no	no	yes

Notes: This table reports estimates from Equation 4. Standard errors clustered at the firm level are reported in parentheses. The significance level is denoted as * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). Dependent variables are drawn from PatentsView and WRDS US Patents and winsorized at the 1st and 99th percentiles. Panel A uses main CPU, measured as the frequency of sentences referencing climate policy uncertainty in firm-quarter earnings calls; Panel B uses negative CPU, measured as the frequency of sentences referencing climate policy uncertainty in a negative tone. Both measures are aggregated to the annual level, normalized to have mean 100, log-transformed, and constructed as the cumulative measure over lags $t-1$ and $t-2$, as defined in Equation 5. CO_2 intensity is sourced from the USEEIO database and is defined at the NAICS-4 level. Controls include Compustat firm characteristics and climate policy salience. Government purchase intensity is defined at the firm-SIC level and downloaded from Baker et al. (2016). All specifications include NAICS-2 and year fixed effects. All logged variables are defined as $\log(1+x)$. The sample consists of firm-year observations with non-missing values for all dependent and independent variables.

implied effect remains modest for total patents but somewhat more negative for clean patents. However, given that the interaction terms are not statistically significant, these differences should be interpreted with caution.

6.3 Job Postings

Finally, job posting results provide complementary evidence to firm-level real outcome regressions. Table 7 shows that higher CPU is associated with declines in both total and green job postings, with larger and more precisely estimated effects under negative CPU. This pattern is consistent with the broader contraction in firm activity documented above.

Green hiring appears especially sensitive to CPU among firms with lower CO_2 intensity, which can be interpreted as firms closer to clean-sector activity. This pattern differs from the real outcome regressions, where employment, R&D, and CAPEX decline more among firms in carbon-intensive sectors. Taken together, the results suggest that high-emissions firms experience larger declines in overall activity, while cleaner firms may adjust more strongly on green hiring.

Job posting results can be interpreted as supporting the overall contractionary effect of CPU, but as providing weaker evidence for the high-emissions heterogeneity mechanism. This difference may be due to the nature of the dependent variable. Job postings measure active hiring demand, while employment captures realized workforce adjustments, including layoffs. Postings may therefore be more sensitive to short-run recruiting conditions and timing decisions, especially for green jobs, which make up a smaller subset of total postings.

Using these table estimates, the implied effect of a 10% increase in (1+CPU) is calculated as

$$\left(1.1^{\beta_1+\beta_2 M_i} - 1\right) \times 100$$

(see Appendix D.2 Equation 9). For a firm with average CO_2 intensity ($M_i = 0$), this results in approximately a 0.17% decline in green job postings and a 0.47% decline in total job

Table 7: Job Postings: Main and Negative CPU

	(1) Green postings	(2) Total postings
Panel A: Main CPU		
$\log(\text{CPU})_{t-1}$	-0.018^{**}	-0.049^{**}
	(0.008)	(0.021)
$\log(\text{CPU})_{t-1} \times \text{CO}_2$ int	0.035	-0.039
	(0.030)	(0.085)
Panel B: Negative CPU		
$\log(\text{CPU}^{-})_{t-1}$	-0.031^{***}	-0.040^{**}
	(0.010)	(0.019)
$\log(\text{CPU}^{-})_{t-1} \times \text{CO}_2$ int	0.079^{***}	0.031
	(0.025)	(0.074)
Observations	25,846	25,851
Firms	1,765	1,765
NAICS-4 FE	yes	yes
Quarter FE	yes	yes

Notes: This table reports estimates from Equation 6. Standard errors clustered at the firm level are reported in parentheses. The significance level is denoted as * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). Dependent variables are drawn from Revelio Labs COSMOS dataset. Panel A uses main CPU, measured as the frequency of sentences referencing climate policy uncertainty in firm-quarter earnings calls; Panel B uses negative CPU, measured as the frequency of sentences referencing climate policy uncertainty in a negative tone. Both measures are aggregated to the quarterly level, normalized to have mean 100, and log-transformed. CO_2 intensity is sourced from the USEEIO database and is defined at the NAICS-4 level. Controls include Compustat firm characteristics and climate policy salience. All specifications include NAICS-4 and quarter fixed effects. All logged variables are defined as $\log(1 + x)$. The sample consists of firm-quarter observations with non-missing values for all dependent and independent variables.

postings using the coefficients in Panel A of Table 7. In response to negative CPU, the decline in green job postings increases to 0.29%, while the decline in total job postings is 0.38%. These calculations indicate that green job postings are more sensitive to negative CPU shocks than to overall CPU shocks.

Results replacing CO_2 intensity with firm-level time-invariant green revenue share are again weaker and inconsistent. While the coefficient is negative, it is not statistically significant, providing only suggestive evidence that cleaner firms' green hiring responds more to CPU (Appendix H).

6.4 Extensions and Additional Results

This paper also estimates several extensions to assess whether the main results are sensitive to alternative measures of firm exposure and directional CPU. First, firm-level green revenue share is used as an alternative moderator, capturing exposure at the clean end of the distribution. The green revenue results are weaker than the CO_2 intensity results: the estimates are generally imprecise and less stable across outcomes. Therefore, green revenue share serves as a suggestive alternative measure of firm exposure rather than as a central source of heterogeneity. These results are reported in Appendix H.

Second, main specifications are estimated using positive CPU. Across real outcomes, patents, and job postings, positive CPU produces weaker and less consistent results than negative CPU. This supports the interpretation that the contractionary effects are more closely associated with adverse or negatively toned CPU. These results are reported in Appendix F.

Third, as an exploratory alternative to the lexicon-based positive and negative CPU measures, this paper classifies matched CPU sentences using sentiment analysis. This exercise requires reconstructing the CPU index from Capital IQ transcripts, which provide the underlying transcript text, as described in Section 3. As a result, the analysis changes both the source and construction of the CPU measure, as well as the definition of directional CPU.

These estimates should be suggestive evidence for the role of sentence tone rather than as a direct robustness test of the main lexicon-based results. The estimates are noisier, but the interaction signs suggest that among firms with green revenue exposure, positive CPU partly attenuates the negative relationship between uncertainty and clean patenting, while negative CPU amplifies it. These results are reported in Appendix I.

7 Conclusion

Climate policy is an important tool for correcting the negative externalities of industrial activity and incentivizing the transition to more sustainable production. However, unclear policy guidance, regulatory instability, and the possibility of policy reversal can generate CPU, potentially delaying firm-level investment and innovation needed for this transition.

This paper contributes to the existing literature by introducing a firm-level measure of CPU that captures firms' perceptions of climate policy from earnings call transcripts. The index covers more than 7,000 U.S. public firms from 2002 to 2025. Validation exercises show that the index co-moves with major climate policy events and is comparable to existing news-based CPU indices when aggregated.

The paper examines how CPU affects firm activity across several margins: investment, measured by capital expenditures; innovation, measured by R&D spending and patenting activity; and employment, measured by the number of employees and new job postings. The analysis also studies heterogeneity by firm exposure to climate policy, focusing on CO_2 intensity in the main specifications, and examines green-sector outcomes using measures of clean patenting and green job postings. Appendix analyses also consider share of green revenue to capture responses among clean firms.

The findings indicate that CPU is associated with economically meaningful changes in firm activity, particularly for more CO_2-intensive firms. Following a 10% increase in CPU, firms with CO_2 intensity one standard deviation above the mean experience a 0.16% decline in employment, a 0.15% decline in capital expenditures, and a 0.67% decline in R&D spending, relative to firms with average CO_2 intensity. Green-sector outcomes also decline. For a firm with average CO_2 intensity, a 10% increase in CPU is associated with a 4.29% decline in clean patenting and a 0.17% decline in green job postings. These results suggest that CPU affects not only traditional firm-level decisions, but also activities directly related to the green transition.

Several limitations remain. First, earnings calls are public-facing communications directed at investors and analysts. As such, they may reflect strategic messaging and may not fully reveal the internal concerns or expectations of firms about future policy. This paper partially addresses this concern by incorporating the Q&A portion of earnings calls, where external participants can ask managers about firm risks. Second, the CPU measure is constructed using a lexicon-based approach, which may not capture all relevant discussions of CPU. Third, the empirical specifications do not include firm fixed effects or industry-by-year fixed effects, which would more fully absorb firm heterogeneity and sector-specific shocks. Future research could address these limitations by incorporating additional text sources, such as post-earnings equity research reports, to capture investor and analyst perspectives; using machine learning methods to improve the classification of CPU discussions; and linking firm-level measures to specific regulatory events. Moreover, given the sparsity of CPU data and limited within-firm variation in outcome samples, future work could use richer data or longer panels.

Overall, the findings point to important policy implications. Ambiguous climate policy can delay firm activity and shift investment away from transition-related efforts, particularly among high-emitting firms that require the greatest structural adjustment. This pattern is consistent with theories of uncertainty in which firms delay costly or irreversible decisions while waiting for policy uncertainty to resolve (Bernanke 1983). Designing climate policy that is not only effective, but also credible is therefore crucial for supporting investment, innovation, and employment in the green transition.

Appendix

A Climate Policy Uncertainty Lexicon

(renewable energy OR electric vehicle OR clean energy OR new energy OR climate change OR wind power OR wind energy OR energy efficient OR greenhouse gas OR solar energy OR air quality OR clean air OR carbon emission OR gas emission OR extreme weather OR carbon dioxide OR water resource OR autonomous vehicle OR energy environment OR wind resource OR battery power OR air pollution OR battery electric OR clean power OR carbon price OR solar farm OR energy regulatory OR heat power OR carbon tax OR onshore wind OR electric motor OR provide energy OR global warm OR power generator OR solar pv OR scale solar OR need clean OR coastal area OR energy star OR environmental footprint OR area energy OR charge station OR clean water OR vehicle manufacturer OR future energy OR motor control OR combine heat OR electric bus OR distribute power OR environmental benefit OR eco friendly OR electrical vehicle OR carbon neutral OR fast charge OR cell power OR energy team OR cycle gas OR coal gasification OR environmental concern OR carbon intensity OR energy application OR produce electricity OR environmental standard OR power agreement OR supply energy OR electric hybrid OR source power OR sustainability goal OR energy reform OR plant power OR compare conventional OR gas vehicle OR effort energy OR carbon free OR electrical energy OR solar installation OR renewable natural OR farm project OR deliver energy OR protect environment OR sustainable energy OR manage energy OR invest energy OR electric energy OR forest land OR capacity energy OR energy AND NOT (human energy OR energy level* OR food energy) OR the environment OR environmental* OR global warming OR climate AND NOT (business climate OR political climate OR economic climate OR regulatory climate OR legal climate OR investment climate OR market climate OR innovation climate) OR carbon OR emission* OR GHG OR CO2 OR methane OR CH4 OR pollut* OR sulphur oxide OR sulfur oxide OR SOx OR sulphur dioxide OR sulfur dioxide OR SO2 OR nitrogen oxide OR NOx OR nitrogen dioxide OR NO2 OR particulate matter OR fine particulates OR fine particle OR PM2.5 OR PM10 OR ozone OR renewable OR hydro OR wind farm OR wind farms OR wind turbine OR wind turbines OR photovoltaic OR PV OR solar OR biomass OR electric vehicles OR electric car OR electric cars OR hybrid vehicle OR hybrid vehicles) AND (policy AND NOT (monetary policy OR national policy OR leasing policy OR tourism policy) OR regulation* OR legislation* OR law OR laws OR fee OR fees OR tax OR taxes OR standard OR standards OR certificate* OR subsidy OR subsidies OR pricing OR ETS OR feed-in-tariff* OR trading scheme OR trading system OR cap and trade OR emissions trading OR label OR eco-label OR mandate OR compliance OR enforcement) AND (risk OR risky OR uncertain OR uncertainty OR risks OR riskier OR unknown OR unpredictability OR risked OR riskiest OR undetermined OR unreliability OR risking OR dangerous OR unsettled OR riskiness OR possibility OR hazardous OR unresolved OR chanciness OR chance OR perilousness OR unsure OR precariousness OR probability OR unsafe OR pending OR unsureness OR likelihood OR insecure OR debatable OR changeability OR danger OR exposed OR unpredictable OR changeableness OR peril OR defenseless OR unforeseeable OR variability OR threat OR precarious OR incalculable OR inconstancy OR menace OR tricky OR speculative OR fitfulness OR fear OR treacherous OR unreliable OR fickleness OR prospect OR untrustworthy OR indecision OR undependable OR irresolution OR hesitancy OR chancy OR dicey OR doubt OR doubtfulness OR instability OR sticky OR hairy OR wavering OR insecurity OR iffy OR vacillation OR dodgy OR equivocation OR gnarly OR changeable OR vagueness OR gamble OR parlous OR variable OR ambivalence OR varying OR disquiet OR irregular OR disquietude OR fitful OR wariness OR jeopardy OR chariness OR hazard OR skepticism OR queries OR unstable OR dubiety OR endanger OR erratic OR incertitude OR imperil OR fluctuating OR jeopardize OR changeful OR tentativeness OR fluctuant OR doubtful OR dubious OR undecided OR diffidence OR irresolute OR uncertainties OR hesitant OR qualm OR misgiving OR apprehension OR quandary OR dilemma OR reservation OR niggle OR scruple OR query OR suspicion OR hesitating OR tentative OR halting OR faltering OR unconfident)

Negative connotation words for Negative CPU (taken from Loughran and McDonald (2011)): (abandon OR abandoned OR abandoning OR abandonment OR abdicate OR aberrant OR abnormal OR abuse OR abusive OR accident OR accuse OR adverse OR adversity OR aggravate OR alienate OR allegation OR annoy OR anomaly OR anticompetitive OR argue OR arrest OR artificial OR assault OR attrition OR bad OR bankrupt OR bankruptcy OR barrier OR bottleneck OR boycott OR breach OR break OR broken OR burden OR burdensome OR calamity OR cancel OR catastrophe OR cease OR censure OR challenge OR collapse OR collusion OR complain OR complicate OR conceal OR concern OR condemn OR conflict OR confuse OR conspiracy OR controversy OR corrupt OR costly OR counterfeit OR crime OR crisis OR critical OR criticism OR cutback OR damage OR danger OR deadlock OR debar OR deceit OR decline OR default OR defeat OR defect OR deficiency OR deficit OR defraud OR degrade OR delay OR delinquency OR demolish OR deny OR depletion OR depress OR deprive OR destabilize OR destroy OR deteriorate OR detract OR detriment OR devastate OR deviate OR difficult OR diminish OR disadvantage OR disagree OR disallow OR disappear OR disappoint OR disapprove OR disaster OR discredit OR disgrace OR dishonest OR disloyal OR dismal OR dismiss OR disorder OR disparage OR dispute OR disqualify OR disregard OR disrupt OR dissatisfaction OR distort OR distract OR distress OR disturb OR divert OR divest OR divorce OR doubt OR downgrade OR downsize OR downturn OR drawback OR drought OR duress OR dysfunction OR embargo OR embarrass OR embezzle OR encroach OR endanger OR erode OR erroneous OR error OR escalate OR evade OR evict OR exacerbate OR exaggerate OR exploit OR expose OR expropriate OR fail OR failure OR false OR falsify OR fault OR fear OR felony OR fine OR fire OR flaw OR force OR foreclose OR forfeit OR fraud OR frustrate OR hardship OR harm OR harass OR harsh OR hazard OR hinder OR hostile OR hurt OR illegal OR illicit OR imbalance OR impair OR impasse OR impede OR imperfect OR impossible OR improper OR imprudent OR inability OR inaccurate OR inaction OR inadequate OR inappropriate OR inattention OR incapable OR incompetent OR incomplete OR inconsistent OR inconvenient OR incorrect OR indecent OR ineffective OR inefficient OR ineligible OR inequitable OR inferior OR infringe OR inhibit OR injure OR insecure OR insolvent OR instability OR insufficient OR interrupt OR invalid OR irregular OR irreversible OR jeopardize OR lack OR lag OR lapse OR late OR lawsuit OR layoff OR liquidate OR litigation OR lockout OR lose OR loss OR malfeasance OR malfunction OR malpractice OR manipulate OR misconduct OR mislead OR mismanage OR misrepresent OR mistake OR monopoly OR negative OR negligence OR noncompliance OR nonperformance OR objection OR obstacle OR obstruct OR offense OR omission OR onerous OR oppose OR outage OR overcharge OR overload OR overpayment OR overrun OR overstate OR panic OR penalty OR peril OR perjury OR persist OR problem OR prosecute OR protest OR provoke OR punish OR questionable OR recall OR recession OR reckless OR redress OR refuse OR reject OR reluctant OR renegotiate OR repossess OR repudiate OR resign OR restate OR restructure OR retaliate OR revoke OR risky OR sabotage OR scandal OR scrutiny OR seize OR serious OR setback OR severe OR shortage OR shutdown OR slander OR slowdown OR stagnation OR stress OR stringent OR subpoena OR suffer OR suspend OR suspicion OR taint OR terminate OR threat OR tortuous OR tragedy OR trouble OR turmoil OR unable OR unacceptable OR unauthorized OR unavailable OR unfair OR unfit OR unforeseeable OR unlawful OR unnecessary OR unpredictable OR unprofitable OR unreliable OR unresolved OR unstable OR unsuccessful OR unsure OR untruthful OR unwarranted OR unwilling OR upset OR urgent OR vandalism OR violate OR violation OR violence OR volatile OR vulnerable OR warn OR waste OR weak OR weakness OR worry OR worsen OR worst OR worthless OR wrong OR wrongdoing)

Positive connotation words for Positive CPU (taken from Loughran and McDonald (2011)): (able OR abundance OR abundant OR acclaimed OR accomplish OR accomplished OR accomplishes OR accomplishing OR accomplishment OR achieve OR achieved OR achievement OR achievements OR achieves OR achieving OR adequately OR advancement OR advancements OR advances OR advancing OR advantage OR advantaged OR advantageous OR advantageously OR advantages OR alliance OR alliances OR assure OR assured OR assures OR assuring OR attain OR attained OR attaining OR attainment OR attains OR attractive OR attractiveness OR beautiful OR beautifully OR beneficial OR beneficially OR benefit OR benefited OR benefiting OR best OR better OR bolstered OR bolstering OR bolsters OR boom OR booming OR boost OR boosted OR breakthrough OR breakthroughs OR brilliant OR charitable OR collaborate OR collaborated OR collaborates OR collaborating OR collaboration OR collaborations OR collaborative OR collaborator OR collaborators OR compliment OR complimentary OR complimented OR complimenting OR compliments OR conclusive OR conclusively OR conducive OR confident OR constructive OR constructively OR courteous OR creative OR creatively OR creativeness OR creativity OR delight OR delighted OR delightful OR delightfully OR delighting OR delights OR dependability OR dependable OR desirable OR desired OR destined OR diligent OR diligently OR distinction OR distinctive OR distinctively OR dream OR easier OR easily OR easy OR effective OR efficiency OR efficient OR efficiently OR empower OR empowered OR empowering OR empowers OR enable OR enabled OR enables OR enabling OR encouraged OR encouragement OR encourages OR encouraging OR enhance OR enhanced OR enhancement OR enhances OR enhancing OR enjoy OR enjoyable OR enjoyed OR enjoying OR enjoyment OR enjoys OR enthusiasm OR enthusiastic OR enthusiastically OR excellence OR excellent OR exceptional OR exceptionally OR excited OR excitement OR exciting OR exclusive OR exclusively OR exemplary OR fantastic OR favorable OR favorably OR favored OR favoring OR favorite OR friendly OR gain OR gained OR gaining OR gains OR good OR great OR greater OR greatest OR greatly OR happiness OR happy OR highest OR honor OR honorable OR honored OR honoring OR ideal OR impress OR impressed OR impresses OR impressing OR impressive OR impressively OR improve OR improved OR improvement OR improves OR improving OR incredible OR incredibly OR influential OR informative OR ingenuity OR innovate OR innovated OR innovates OR innovating OR innovation OR innovations OR innovative OR insightful OR inspiration OR inspirational OR integrity OR invent OR invented OR inventing OR invention OR inventions OR inventive OR inventor OR inventors OR leadership OR leading OR loyal OR lucrative OR meritorious OR opportunity OR optimistic OR outperform OR outperformed OR outperforming OR outperforms OR perfect OR perfected OR perfectly OR pleasant OR pleased OR pleasure OR plentiful OR popular OR popularity OR positive OR positively OR preeminent OR prestige OR prestigious OR proactive OR proficiency OR proficient OR profitability OR profitable OR progress OR progressed OR progresses OR progressing OR prosperity OR prosperous OR rebound OR rebounded OR regain OR regained OR resolve OR revolutionize OR reward OR rewarded OR rewarding OR rewards OR satisfaction OR satisfactory OR satisfied OR satisfy OR satisfying OR smooth OR smoothly OR solve OR solving OR spectacular OR stability OR stabilize OR stabilized OR stable OR strength OR strengthen OR strengthened OR strong OR stronger OR strongest OR succeed OR succeeded OR succeeds OR success OR successful OR successfully OR superior OR surpass OR surpassed OR surpasses OR transparency OR tremendous OR tremendously OR unmatched OR unparalleled OR unsurpassed OR upturn OR upturns OR valuable OR versatile OR vibrant OR win OR winner OR winning OR worthy)

B Negative and Positive CPU Earnings Call Snippets

Table 8: Snippets of Top Negative Climate Policy Uncertainty Exposure Firms

Firm	SIC	Time	Snippet
International Isotopes Inc	3823	2011Q2	Those risks include, among other things, the loss of market share through competition or otherwise; the introduction of competing technologies by other companies; new governmental safety, health and environmental regulations which could require International Isotopes to make significant capital expenditures.
Babcock & Wilcox Enterprises Inc	3433	2018Q4	This was primarily due to the anticipated lower revenue on retrofit contracts in the U.S. and delays in projects caused by uncertainty in U.S. environmental regulations, such as the coal combustion residual regulations.
First Solar Inc	3674	2024Q2	While the current environment, if allowed to persist, will provide a short-term pricing benefit to developers, allowing these practices to continue denies non-Chinese solar manufacturers the opportunity to scale and compete on a level playing field while multiplying installers and developers exposure to the risk of over-concentrated supply chains.

Notes: This table reports selected excerpts from firm earnings call transcripts that mentions climate policy uncertainty in a negative tone.

Table 9: Snippets of Top Positive Climate Policy Uncertainty Exposure Firms

Firm	SIC	Time	Snippet
AZZ Inc	3643	2004Q3	Project related to wind energy have been delayed due to pending legislation, however, we are in a good position to benefit should growth occur in this market sector.
Piedmont Natural Gas Company Inc	4924	2010Q1	We're still optimistic about the ultimate chance to modify rate design to be consistent with the energy policy in the state.
Alico Inc	0174	2024Q3	With his public policy and public service experience, Adam brings to the Board expertise in understanding and navigating the physical and transition risks and opportunities of climate change together with his knowledge of sustainability, water supply and agriculture operations within Florida's regulatory environment.

Notes: This table reports selected excerpts from firm earnings call transcripts that mentions climate policy uncertainty in a positive tone.

C Variance decomposition

To understand the sources of variation in the firm-quarter CPU index, an incremental variance decomposition is performed based on sequential increases in R^2. First, a model with time fixed effects only is estimated, where R^2 captures the share of variation explained by aggregate time shocks relative to a constant-only model. Second, industry fixed effects are added; the incremental increase in R^2 reflects variation explained by cross-industry differences beyond common time effects. Third, the additive specification is replaced with industry-by-time fixed effects; the additional R^2 captures sector-specific shocks over time. Finally, the remaining unexplained variation is attributed to firm-level factors, computed as one minus the sum of the preceding components.

Table 10 reports the results. Common time effects explain only 0.1% of the variation, while additive industry effects account for 0.8%, and industry-by-time effects contribute an additional 0.5%. These findings suggest that CPU variation is mainly idiosyncratic across firms, as the remaining 98.6% is residual variation not explained by the aforementioned factors.

Table 10: Incremental Variance Decomposition of Firm-Level CPU

Component	Percent
Time FE	0.1
Industry FE (additive)	0.8
Industry $\times$ Time FE	0.5
Firm-level (residual)	98.6

Notes: This table reports an incremental variance decomposition of firm-level CPU. Percent corresponds to the incremental R^2 obtained by sequentially adding fixed effects, expressed in percentage terms and rounded to the nearest decimal.

D Interpreting coefficient magnitudes

D.1 OLS interpretation

To interpret the magnitude of the estimated coefficients, note that all logarithmic transformations are defined as $\log(1+x)$. Consider a counterfactual change in $\mathrm{CPU}^{(s)}_{i,t-1}$ from an initial level $\mathrm{CPU}^{(s)}_{i,t-1}$ to a new level $\mathrm{CPU}^{(s)\prime}_{i,t-1}$, holding all else constant. From equation (3), the change in the outcome is:

$$\Delta y_{it} = (\beta_1 + \beta_2 M_i)\left[\log\Big(1+\mathrm{CPU}^{(s)\prime}_{i,t-1}\Big) - \log\Big(1+\mathrm{CPU}^{(s)}_{i,t-1}\Big)\right].$$

Using log rules, this can be rewritten as:

$$\Delta y_{it} = (\beta_1 + \beta_2 M_i)\log\left(\frac{1+\mathrm{CPU}^{(s)\prime}_{i,t-1}}{1+\mathrm{CPU}^{(s)}_{i,t-1}}\right).$$

Exponentiating both sides yields:

$$\frac{1+Y'_{it}}{1+Y_{it}} = \left(\frac{1+\mathrm{CPU}^{(s)\prime}_{i,t-1}}{1+\mathrm{CPU}^{(s)}_{i,t-1}}\right)^{\beta_1+\beta_2 M_i}.$$

The implied percent change in the outcome is approximately:

$$\%\Delta Y_{it} = \left[\left(\frac{1+\mathrm{CPU}^{(s)\prime}_{i,t-1}}{1+\mathrm{CPU}^{(s)}_{i,t-1}}\right)^{\beta_1+\beta_2 M_i} - 1\right]\times 100. \tag{7}$$

D.2 PPML interpretation

From equation (4), the conditional mean is:

$$\mathbb{E}[y_{it}\mid X] = \exp\Big(\beta_1\,\mathrm{CPU}^{(s)}_{it,\mathrm{sum12}} + \beta_2\,\mathrm{CPU}^{(s)}_{it,\mathrm{sum12}}\times M_i + \cdots\Big),$$

where

$$\mathrm{CPU}^{(s)}_{it,\mathrm{sum12}} = \log(1+\mathrm{CPU}_{i,t-1}) + \log(1+\mathrm{CPU}_{i,t-2}).$$

Consider a change in CPU driven by changes in $\text{CPU}_{i,t-1}$ and $\text{CPU}_{i,t-2}$, holding all else constant. The resulting change in the cumulative regressor is:

$$\Delta\text{CPU}^{(s)}_{it,\text{sum12}} = \log\left(\frac{1+\text{CPU}'_{i,t-1}}{1+\text{CPU}_{i,t-1}}\right) + \log\left(\frac{1+\text{CPU}'_{i,t-2}}{1+\text{CPU}_{i,t-2}}\right).$$

This can be written as:

$$\Delta\text{CPU}^{(s)}_{it,\text{sum12}} = \log\left(\frac{(1+\text{CPU}'_{i,t-1})(1+\text{CPU}'_{i,t-2})}{(1+\text{CPU}_{i,t-1})(1+\text{CPU}_{i,t-2})}\right).$$

The implied change in expected outcomes is:

$$\frac{\mathbb{E}[y_{it} \mid X, \Delta]}{\mathbb{E}[y_{it} \mid X]} = \exp\Big[(\beta_1 + \beta_2 M_i)\, \Delta\text{CPU}^{(s)}_{it,\text{sum12}}\Big].$$

Substituting yields:

$$\frac{\mathbb{E}[y_{it} \mid X, \Delta]}{\mathbb{E}[y_{it} \mid X]} = \left(\frac{(1+\text{CPU}'_{i,t-1})(1+\text{CPU}'_{i,t-2})}{(1+\text{CPU}_{i,t-1})(1+\text{CPU}_{i,t-2})}\right)^{\beta_1+\beta_2 M_i}.$$

Therefore, the implied percent change in expected patent outcomes is:

$$\%\Delta y_{it} = \left[\left(\frac{(1+\text{CPU}'_{i,t-1})(1+\text{CPU}'_{i,t-2})}{(1+\text{CPU}_{i,t-1})(1+\text{CPU}_{i,t-2})}\right)^{\beta_1+\beta_2 M_i} - 1\right] \times 100. \tag{8}$$

If we consider equation (6), with lag-1 CPU, the implied percent change in expected job postings becomes:

$$\%\Delta y_{it} = \left[\left(\frac{1+\text{CPU}'_{i,t-1}}{1+\text{CPU}_{i,t-1}}\right)^{\beta_1+\beta_2 M_i} - 1\right] \times 100. \tag{9}$$

E Real Outcomes: Robustness Checks

Table 11: Outcome OLS Robustness: Main, Negative, and Positive CPU

	EPU × Gov purchase int			NAICS-2 FE		
	(1) log(Emp)	(2) log(R&D)	(3) log(CAPEX)	(4) log(Emp)	(5) log(R&D)	(6) log(CAPEX)
Panel A: Main CPU						
$\log(\text{CPU})_{t-1}$	−0.007	−0.013	0.0004	−0.003	−0.026**	0.002
	(0.005)	(0.012)	(0.006)	(0.008)	(0.011)	(0.006)
$\log(\text{CPU})_{t-1} \times CO_2$ int	−0.015**	−0.073***	−0.015*	−0.023**	−0.037**	−0.019*
	(0.006)	(0.015)	(0.009)	(0.012)	(0.017)	(0.011)
Panel B: Negative CPU						
$\log(\text{CPU}^-)_{t-1}$	−0.008	−0.019	−0.002	−0.003	−0.035**	−0.001
	(0.006)	(0.016)	(0.005)	(0.011)	(0.014)	(0.005)
$\log(\text{CPU}^-)_{t-1} \times CO_2$ int	−0.017***	−0.077***	−0.017***	−0.016*	−0.035**	−0.016**
	(0.005)	(0.014)	(0.006)	(0.010)	(0.016)	(0.008)
Panel C: Positive CPU						
$\log(\text{CPU}^+)_{t-1}$	0.001	−0.002	0.008	−0.009	−0.013	−0.002
	(0.006)	(0.010)	(0.008)	(0.010)	(0.012)	(0.010)
$\log(\text{CPU}^+)_{t-1} \times CO_2$ int	−0.016	0.010	−0.041*	−0.078***	0.017	−0.066*
	(0.013)	(0.027)	(0.025)	(0.025)	(0.038)	(0.038)
Observations	21,729	21,953	21,966	25,145	25,417	25,435
Firms	2,219	2,232	2,230	3,115	3,127	3,133
EPU × Gov purchase int	yes	yes	yes	no	no	no
NAICS-2 FE	no	no	no	yes	yes	yes
NAICS-4 FE	yes	yes	yes	no	no	no
Year FE	yes	yes	yes	yes	yes	yes

Notes: This table reports estimates from Equation 3. Panel A uses main CPU, Panel B uses negative CPU, and Panel C uses positive CPU. Standard errors clustered at the firm level are reported in parentheses. Statistical significance is denoted by * ($p < 0.10$), ** ($p < 0.05$), and *** ($p < 0.01$). Government purchase intensity is defined at the firm-SIC level and downloaded from Baker et al. (2016).

F Positive CPU: Additional Results

Table 12: Outcome OLS: Positive CPU

	(1) log(Emp)	(2) log(R&D)	(3) log(CAPEX)
$\log(\text{CPU}^{+})_{t-1}$	-0.0005	-0.003	0.006
	(0.006)	(0.010)	(0.008)
$\log(\text{CPU}^{+})_{t-1} \times$ CO2 int	-0.021	0.011	-0.041^{*}
	(0.014)	(0.027)	(0.025)
Observations	24,778	25,046	25,061
Firms	3,064	3,076	3,082
NAICS-4 FE	yes	yes	yes
Year FE	yes	yes	yes

Notes: This table reports OLS estimates from Equation 3 using positive CPU. The specification follows Table 4. Standard errors clustered at the firm level are reported in parentheses. The significance level is denoted as * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table 13: Patenting: Positive CPU

	(1) Total patents	(2) Clean patents	(3) Clean patents
$\log(\text{CPU}^{+})_{t-1,t-2}$	-0.195^{***}	-0.251^{***}	-0.248^{**}
	(0.062)	(0.095)	(0.098)
$\log(\text{CPU}^{+})_{t-1,t-2} \times$ CO2 int	-0.154	-0.179	-0.186
	(0.299)	(0.205)	(0.164)
Observations	883	881	868
Firms	113	112	109
NAICS2 FE	yes	yes	yes
Year FE	yes	yes	yes
EPU $\times$ firm SIC int	no	no	yes

Notes: This table reports PPML estimates from Equation 4 using positive CPU. The specification follows Table 6. Standard errors clustered at the firm level are reported in parentheses. Significance levels are denoted as * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table 14: Job Postings: Positive CPU

	(1) Green postings	(2) Total postings
$\log(\text{CPU}^{+})_{t-1}$	-0.009	-0.044^{**}
	(0.009)	(0.018)
$\log(\text{CPU}^{+})_{t-1} \times$ CO2 int	0.083^{***}	-0.042
	(0.020)	(0.060)
Observations	25,846	25,851
Firms	1,765	1,765
NAICS-4 FE	yes	yes
Quarter FE	yes	yes

Notes: This table reports PPML estimates from Equation 6 using positive CPU. The specification follows Table 7. Standard errors clustered at the firm level are reported in parentheses. Significance levels are denoted as * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

G Patenting: Lag Robustness

Table 15: Patenting: Alternative Lag Structure

	(1) Total patent	(2) Clean patent	(3) Clean patent
Panel A: Main CPU			
$\log(\text{CPU})_{t-2}$	-0.140^{**}	-0.269^{***}	-0.271^{***}
	(0.055)	(0.073)	(0.077)
$\log(\text{CPU})_{t-2} \times CO_2$ int	0.127	0.044	-0.027
	(0.143)	(0.228)	(0.188)
Panel B: Negative CPU			
$\log(\text{CPU}^{-})_{t-2}$	-0.161^{***}	-0.344^{***}	-0.357^{***}
	(0.046)	(0.112)	(0.131)
$\log(\text{CPU}^{-})_{t-2} \times CO_2$ int	0.091	-0.084	-0.096
	(0.133)	(0.206)	(0.173)
Panel C: Positive CPU			
$\log(\text{CPU}^{+})_{t-2}$	-0.200^{***}	-0.361^{***}	-0.367^{***}
	(0.053)	(0.120)	(0.128)
$\log(\text{CPU}^{+})_{t-2} \times CO_2$ int	0.011	-0.085	-0.144
	(0.154)	(0.223)	(0.175)
Observations	897	895	882
Firms	114	113	110
NAICS-2 FE	yes	yes	yes
Year FE	yes	yes	yes
EPU × firm SIC int	no	no	yes

Notes: This table reports PPML estimates from Equation 4, replacing the cumulative CPU measure with the second lag of CPU. Panel A uses main CPU, Panel B uses negative CPU, and Panel C uses positive CPU. The specification follows Table 6. Standard errors clustered at the firm level are reported in parentheses. Significance levels are denoted as * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

H Heterogeneity by Green Revenue Share

Table 16: Outcome OLS: Main CPU

	(1) log(Emp)	(2) log(R&D)	(3) log(CAPEX)
$\log(\text{CPU})_{t-1}$	0.008	-0.015	-0.008
	(0.007)	(0.016)	(0.008)
$\log(\text{CPU})_{t-1} \times$ Green Rev	-0.0003	-0.001	0.0002
	(0.0002)	(0.0004)	(0.0002)
Observations	17,211	17,390	17,405
Firms	1,636	1,634	1,640
NAICS-4 FE	yes	yes	yes
Year FE	yes	yes	yes

Notes: This table reports estimates from Equation 3, using firm-level green revenue share (LSEG) as the moderator. Standard errors are clustered at the firm level. Significance levels are denoted as * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table 17: Job Postings: Main CPU

	(1) Green postings	(2) Total postings
$\log(\text{CPU})_{t-1}$	-0.005	-0.053^{***}
	(0.008)	(0.013)
$\log(\text{CPU})_{t-1} \times$ Green Rev	-0.0002	0.002^{**}
	(0.0002)	(0.001)
Observations	27,033	27,033
Firms	1,531	1,531
NAICS-4 FE	yes	yes
Quarter FE	yes	yes

Notes: This table reports estimates from Equation 6, using firm-level green revenue share (LSEG) as the moderator. Standard errors are clustered at the firm level. Significance levels are denoted as * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

I Alternative CPU Decomposition: Sentiment Analysis

In addition to the lexicon-based sentiment split, this paper also leverages sentiment analysis to classify the tone of each sentence. A lexicon-based approach may be limited because the presence of a positive or negative word does not necessarily indicate the attitude of the sentence. A Large Language Model is used to conduct sentiment analysis on each matched sentence containing all three keyword categories, along with surrounding context from the two sentences before and after it. The model classifies each matched sentence as either overall positive or negative. Positive CPU is then defined as the frequency of matched sentences with a positive tone in earnings calls, while negative CPU is defined analogously. By construction, positive and negative CPU sum to the main CPU measure.

Table 18 reports patent regressions using sentiment subindices. These results are preliminary, but suggest that green revenue exposure moderates the relationship between CPU sentiment and clean innovation. Positive CPU is associated with a less negative clean patenting response among green-exposed firms, while negative CPU is associated with a more negative response.

Table 18: Patenting: Sentiment-Based CPU

	(1) Total patent	(2) Clean patent	(3) Clean patent
Panel A: Negative Sentiment CPU			
$\log(\text{CPU}^{-})_{t-1,t-2}$	-0.150^{*}	-0.057	-0.013
	(0.083)	(0.160)	(0.127)
$\log(\text{CPU}^{-})_{t-1,t-2} \times$ Green Rev	0.004^{*}	-0.002	-0.004
	(0.003)	(0.004)	(0.004)
Panel B: Positive Sentiment CPU			
$\log(\text{CPU}^{+})_{t-1,t-2}$	-0.181^{**}	-1.803^{***}	-1.809^{***}
	(0.088)	(0.072)	(0.066)
$\log(\text{CPU}^{+})_{t-1,t-2} \times$ Green Rev	0.006^{***}	0.022^{***}	0.022^{***}
	(0.002)	(0.002)	(0.002)
Observations	532	523	523
Firms	72	68	68
NAICS-2 FE	yes	yes	yes
Year FE	yes	yes	yes
EPU × firm SIC int	no	no	yes

Notes: This table reports estimates from Equation 4 using CPU constructed through sentiment analysis. Panel A uses negative sentiment CPU, and Panel B uses positive sentiment CPU. The specification follows Table 6. Standard errors clustered at the firm level are reported in parentheses. The significance level is denoted as * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

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