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Climate policy uncertainty and analyst forecast quality for greenhouse gas-intensive firms

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ABSTRACT

This study examines the impact of climate policy uncertainty (CPU) on financial analysts' ability to forecast the performance of greenhouse-gas (GHG)-intensive firms. We measure CPU using the Gavriilidis (2021) CPU index, which we validate by confirming its correlation with climate-related legislative activities and its distinction from general economic uncertainty indices. Our findings reveal that CPU negatively impacts forecast quality, increasing dispersion and reducing accuracy, especially for long-term earnings forecasts. Political gridlock, characterized by a divided government and ideological polarization in Congress, mitigates the negative effects of CPU. Furthermore, GHG-intensive firms with higher-quality financial disclosures and those followed by more skilled analysts experience less deterioration in forecast quality due to CPU. Finally, GHG-intensive firms that increase climate-related discussions during earnings calls in periods of high CPU mitigate the adverse impact on forecast quality.

1. Introduction

The SEC's recent ruling on climate risk disclosure aims to help investors better assess firms vulnerable to climate change, particularly those that are greenhouse gas (GHG)-intensive (U.S. Securities and Exchange Commission, 2024). While the ruling addresses financial and physical risks, it overlooks a critical factor: climate policy uncertainty (CPU). CPU involves the unpredictability of policy changes, their timing, and the challenges firms face in balancing short-term costs with long-term gains in reducing emissions. This uncertainty is exacerbated by public perception and political polarization, leading to inconsistent policy support. Consequently, GHG-intensive firms are especially at risk due to their reliance on capital-intensive infrastructure, which limits their flexibility in responding to regulatory shifts. Despite the importance of CPU, few studies have examined its impact on market perceptions of these firms. This study seeks to address this gap by documenting the economic consequences of CPU on GHG-intensive firms, particularly its negative effect on market expectations, as reflected in financial analysts' forecasts.

To operationalize the construct of CPU, we utilize a monthly, time-varying CPU index developed by Gavriilidis (2021), which is based on a comprehensive text search of eight major US newspapers for climate policy-related terms. Unlike previous research that focuses on specific legislative events, our study views CPU as a dynamic process influenced by factors such as political gridlock, electoral cycles, prolonged litigation, and shifting rulings from executive and judicial branches. Recognizing that Gavriilidis' index is relatively new and not extensively vetted in academic literature, our analysis begins with its validation. We aim to (1) confirm that the CPU index correlates with actual climate-related legislative activities, and (2) ensure it is not merely a proxy for other general uncertainty indices, such as Baker, Bloom, and Davis's (2016) economic uncertainty index. Our validation confirms that the CPU index accurately captures climate-specific policy uncertainty, demonstrating a strong correlation with legislative activities like bill introductions and

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congressional hearings. Moreover, the analysis shows that the CPU index reflects a distinct source of uncertainty, separate from general economic policy uncertainties.

After validating the CPU index, we assess its impact on analysts' forecast quality for GHG-intensive firms, identified as those subject to the Greenhouse Gas Reporting Program.[1,2] We measure forecast quality through the dispersion and accuracy of analysts' predictions for one-year-ahead earnings and long-term growth rates. Our regression results show that CPU negatively impacts forecast quality, leading to greater dispersion and reduced accuracy, with a more pronounced effect on long-term earnings forecasts. These findings suggest that CPU poses significant challenges for analysts, especially in making long-term predictions.

Next, we examine whether the impact of CPU varies with the macro-level political environment and micro-level firm characteristics. At the macro level, we assess how political gridlock affects the relationship between CPU and forecast quality. Political gridlock is defined as legislative paralysis caused by split control of the executive and legislative branches, along with ideological differences between major parties. Our findings suggest that political gridlock reduces analysts' concern about sudden changes in climate-related policies. This finding aligns with the idea that, while gridlock is typically seen as an obstacle to policy progress, it can unintentionally create a more stable environment for market participants. This underscores the complex interplay between political dynamics and market stability (Binder 2004; Byrne, 2004).

At the micro level, we investigate whether the quality of financial disclosures by GHG-intensive firms and the expertise of their analysts independently mitigate the negative impact of CPU on forecast quality. Our results indicate that higher disclosure quality lessens the adverse effect of CPU on forecast accuracy, emphasizing the crucial role of transparent and comprehensive corporate disclosures in helping analysts and investors navigate uncertainties. Moreover, we find that analysts' expertise in assessing and interpreting macroeconomic information further mitigates the impact of CPU on forecast quality. This suggests that more skilled analysts, particularly those with deeper macroeconomic knowledge, are better equipped to anticipate the various outcomes of macro-level government policies and their impact on firms' fundamentals.

Lastly, prior theoretical studies suggest that managers voluntarily disclose information beyond mandatory reporting requirements to ease market concerns about the distribution of future cash flows (Diamond & Verrecchia, 1991; Verrecchia, 1983, 2001). We apply this theory to the context of climate policy by examining (1) whether firms increase voluntary disclosures during periods of heightened climate policy uncertainty and (2) whether such enhanced disclosure mitigates the impact of CPU on analyst forecast quality. Using the extent of climate-related discussion during quarterly earnings calls as a proxy for voluntary disclosure by GHG-intensive firms, we find evidence that managers are more likely to engage in climate-related discussions with financial analysts and other participants during times of greater uncertainty. Moreover, these increased discussions are linked to a reduced impact of CPU on analyst forecast quality. This suggests that proactive communication by firms can help manage the uncertainties associated with volatile climate policies.

Our study contributes significantly to the existing literature. First, we advance emerging research on how firms' climate risk influences analyst forecasts. Previous studies, such as those by Kong, Lin, Wang, and Xiang (2021) and Tran, Truong, and Zhao (2020), have demonstrated that extreme weather events amplify analysts' perceptions of firms' climate risks. Similarly, Zhang and Kanagaretnam (2024) and Pankratz, Bauer, and Derwall (2023) observed greater divergence and more errors in analyst expectations for firms exposed to abnormal weather conditions. We build on this line of research by showing that policy-related climate risks, especially the unpredictability of regulatory outcomes, can significantly impact analyst forecast quality, leading to greater dispersion and reduced accuracy in both short- and long-term earnings predictions. Additionally, our findings highlight an important opportunity for regulators: by expanding these disclosure requirements to include potential impacts and strategies in response to evolving government climate policies, the SEC could significantly enhance the value of this information for market participants, thereby improving market stability and informed decision-making.

Second, we contribute to the literature that offers varying perspectives on the market consequences of political gridlock, largely due to the different ways gridlock is defined or measured. In finance and accounting literature, gridlock is often proxied by divided government—where the presidency and Congress are controlled by different parties—and is typically linked to increased stock return volatility (Beyer, Jensen, & Johnson, 2006; Cheng, 2022). This perspective suggests that political gridlock complicates legislative progress, thereby intensifying market uncertainty regarding future policy developments. In contrast, political scientists argue that gridlock is better understood as the result of the interplay between divided government and partisan preferences (Binder, 1999; Fiorina & Abrams, 2008; McCarty & Razaghian, 1999). Specifically, the Congress is more susceptible to gridlock when divided government coincides with polarized political ideologies. We follow this literature to measure political gridlock and demonstrate that while it hinders legislative progress, gridlock may inadvertently simplify analysts' assessments of GHG-intensive firms' fundamentals during periods of climate policy uncertainty.

Finally, our study highlights how macro-level policy uncertainty interacts with micro-level factors to influence market assessments of firms' fundamentals. Previous empirical research has explored how the effects of economic policy uncertainty vary based on firm-specific characteristics, such as voluntary disclosure practices (e.g., Choi, Gallo, Hann, & Kim, 2024; Nagar, Schoenfeld, & Wellman, 2019), political activities (e.g., Akey & Lewellen, 2017; Christensen, Jin, Sridharan, & Wellman, 2022), and the expertise of the analysts covering these firms (e.g., Baloria & Mamo, 2017; Chourou, Purda, & Saadi, 2021; Dai, Ding, & Zhang, 2024). We build on this research by demonstrating that firms particularly vulnerable to climate policy uncertainty—such as GHG-intensive firms—experience less impact from this uncertainty when they maintain transparent financial disclosures, are covered by skilled analysts, and engage proactively in communication with financial analysts.

The remainder of the study is organized as follows: Section 2 outlines our hypotheses based on prior research, Section 3 details our data, and Sections 4 and 5 present our empirical results. Finally, Section 6 provides our conclusion.

2. Prior literature review & hypothesis development

2.1. Climate policy uncertainty

We define CPU as the specific uncertainties related to climate policy, distinguishing it from broader economic policy uncertainty. CPU captures the unpredictability of potential changes in climate regulations,

[1] See section 3.2. Sample Selection and Sample Distribution for more detailed.

[2] Two alternative approaches are available to identify GHG-intensive firms. The first approach is to rely on firm's voluntary disclosure of carbon emissions. For example, Ben-Amar & McIlkeny (2015), Lee, Park, and Klassen (2015) and Stanny (2013) capture the firm's voluntary disclosure based on the firm's decision to voluntarily respond to the Carbon Disclosure Project (www.cdp.net) annual questionnaire. The second approach is to utilize proprietary data. For instance, Ardia, Bluteau, Boudt, and Inghelbrecht (2023) identify the firm's green-ness based on ASSET4/Refinitiv carbon-dioxide-equivalent greenhouse gas emission data. Due to data limitation, we acknowledge but do not examine the robustness of our findings based on the alternative approaches.

the timing and enforcement of these changes, and the challenges firms face in balancing short-term costs with uncertain long-term benefits associated with reducing greenhouse gas emissions.

While climate policies often overlap with other government policies or form part of broader economic policy packages, uncertainty related to climate policy is uniquely distinct from other types of policy uncertainty. This distinction arises because climate policy development is heavily influenced by scientific models that project future climate conditions and recommend necessary actions to mitigate or adapt to climate change. These scientific models are inherently uncertain due to the complexity of the climate system and the unpredictability of various factors, such as greenhouse gas emissions, technological advancements, and socio-economic changes (e.g., Hallegatte, Shah, Brown, Lempert, & Gill, 2012). For example, in March 2023, the Intergovernmental Panel on Climate Change (IPCC) released an assessment warning of the devastating consequences of rising anthropogenic GHG emissions globally and the increasingly dangerous and irreversible risks if countries fail to change course (Intergovernmental Panel on Climate Change, 2023). This assessment was based on over 1500 potential GHG emission scenarios, ranging from '*most optimistic*' to '*avoid at all costs*.' These scenarios were derived from simulations using more than 50 complex climate models, incorporating a wide range of assumptions about numerous unpredictable factors, including policy decisions, technological advancements, and socio-economic changes. Importantly, the IPCC acknowledges that it is not possible to assign a likelihood to any specific emissions scenario and that the associated uncertainties are best represented by the full range of scenarios.

Climate policy uncertainty is also affected by public perception of climate science. If scientific findings are met with skepticism or politicized, it can lead to inconsistent policy support and implementation, further contributing to uncertainty. A recent survey shows that nearly 90 % of Democrats say reducing the effects of climate change needs to be "*a top priority to ensure a sustainable planet for future generations, even if that means fewer resources for addressing other important problems today*" (Pew Research Center, 2023). In contrast, 61 % of Republicans say that efforts to reduce the effects of climate change should be a lower priority. The stark partisan view complicates the direction of climate policies. For example, most Democrats (90 %) view developing alternative energy source – including wind and solar power – as the more important priority for addressing America's energy supply and GHG emission. On the other hand, more than half (52 %) of Republicans support expanding offshore oil drilling, hydraulic fracturing, and coal mining.

Lastly, the development of climate policies is often closely intertwined with international agreements to combat climate change, adding an additional layer of uncertainty.[3] International agreements often face challenges or failures due to disagreements over the distribution of responsibilities and financial burdens between developed and developing countries can lead to contentious negotiations and vague commitments. Furthermore, many international agreements lack strong enforcement mechanisms. Without penalties for non-compliance, political leaders may lack the will to take decisive actions on climate change and succumb to lobbying by powerful industries, public opinion, or other pressing economic issues. For example, in March 2017, former President Trump announced that the U.S. would withdraw from the Paris Agreement, a global accord aimed at reducing greenhouse gas emissions to combat climate change. Trump described the agreement as unfair to the United States, arguing that it imposed economic burdens, such as job losses and factory closures, while benefiting other countries (The White House, 2017).

In summary, CPU encompasses the unpredictability of climate policy changes, shaped by complex scientific models, public perception, and political polarization. This uncertainty is further intensified by inconsistent policy support and weak enforcement mechanisms in international agreements. Unlike general economic policy uncertainty, CPU is uniquely tied to the evolving and complex nature of climate science and international cooperation, making it a distinct and challenging factor for firms to navigate.

2.2. *Climate policy uncertainty and quality of financial analyst forecast for GHG-intensive firms*

We explore how climate policy uncertainty influences financial analyst forecasts for firms with high greenhouse gas emissions. We focus on the GHG-intensive firms as they face heightened media scrutiny and shareholder activism due to their significant role in climate change, making them especially susceptible to changes in climate policy (e.g., Boykoff & Roberts, 2007; Clark & Crawford, 2012; Flammer, Toffel, & Viswanathan, 2021; Reid & Toffel, 2009). Additionally, their reliance on capital-intensive infrastructure limits their flexibility in adapting to unpredictable regulatory changes (e.g., Wang, Wu, & Zhang, 2022). This uncertainty complicates investors' and analysts' ability to accurately assess these firms' future prospects.

Theoretical frameworks suggest that uncertainty around policy changes deteriorates the information environment for market participants, particularly financial analysts, thereby reducing the quality of their assessments of firms' future cash flows and profitability (Harris & Raviv, 1993; Kandel & Pearson, 1995; Varian, 1985, 1989). This has been empirically supported in contexts such as presidential election cycles (Baloria & Mamo, 2017), Federal Open Market Committee meetings (Hope, Liu, & Zhang, 2022), tax policies (Brown, Lin, Moore, & Wellman, 2022), and general economic policies (Chourou et al., 2021). Given that climate policies significantly impact the fundamentals of GHG-intensive firms (e.g., Blyth et al., 2007; Huang & Sun, 2023), we expect that climate policy uncertainty will similarly reduce the quality of analyst forecasts for these firms, leading to increased forecast dispersion and reduced accuracy.

However, there are reasons to believe that CPU may not significantly affect analyst forecast quality. Analysts must not only evaluate potential changes in climate policies and related regulatory actions but also assess how these changes may impact specific firms' fundamentals. When the forecasting task becomes overly complex, analysts might struggle to update their expectations (e.g., Chan, 2022; Plumlee, 2003) and may resort to herding behavior (e.g., Clement & Tse, 2005; Hong, Kubik, & Solomon, 2000), which could result in little to no change—or even a reduction—in forecast dispersion. Additionally, firms may implement strategies to mitigate the effects of CPU, such as engaging in political activities, increasing voluntary disclosure, or postponing capital expenditures (Bhattacharya, Hsu, Tian, & Xu, 2017; Julio & Yook, 2012; Nagar et al., 2019; Shang, Lin, & Saffar, 2021). If such management interventions effectively reduce the impact of policy uncertainty on the firm, we may not observe the anticipated decline in analyst forecast accuracy.

Despite mixed insights from prior literature on the impact of CPU on analyst forecast quality, we posit that financial analysts grapple with the complexities and uncertainties inherent in predicting climate policy outcomes, undermining their forecast quality. In particular, our main prediction is that:

HYPOTHESIS 1: Climate policy uncertainty is negatively associated with financial analyst forecast quality

[3] In December 2015, the U.S. joined the Paris Agreement, aiming to limit global warming to well below 2 degrees Celsius above pre-industrial levels. This commitment involved implementing domestic policies to transition towards cleaner energy sources, improve energy efficiency, and reduce carbon emissions across various sectors. For instance, under Obama administration, the Clean Power Plan aimed to reduce carbon emissions from power plants, a key component of the U.S. commitment to the Paris Agreement. Additionally, Biden's administration introduced ambitious climate policies, including the American Jobs Plan and the Build Back Better framework, which focus on renewable energy investments, electric vehicle infrastructure, and carbon reduction targets aligned with the Paris Agreement goals.

2.3. Cross-sectional analyses

2.3.1. Political gridlock

Political science literature suggests that political gridlock—characterized by split party control of the executive and legislative branches—can substantially impact how policy uncertainty affects market participants, particularly financial analysts, in their assessments of firms' long-term prospects. The rationale is that political gridlock often hinders substantial policy advancements, reducing the likelihood of disruptive legislative changes and thereby inadvertently stabilizing sectors sensitive to policy shifts. Edwards, Barrett, and Peake (1997) find that significant legislation is more likely to fail under divided government than when one party controls both branches. Similarly, Binder (1999) develops a measure of the legislative agenda and observed that agenda items are more likely to fail in a divided government. Moreover, Brownstein (2007) and Mann and Ornstein (2016) highlight how increasing polarization between parties has intensified gridlock, making it increasingly difficult to pass even routine legislation. This contributes to market predictability, as noted by Binder (2004) and Byrne (2004).

Volden and Wiseman (2011) propose that polarization over key issues exacerbates political gridlock, with anthropogenic climate change being a prime example (Fisher, Waggle, & Leifeld, 2013; Gamble, 2019; Turner, 2018). Despite decades of scientific consensus on human-driven climate change, political divisions have deepened, leading to starkly polarized ideologies between the Democratic and Republican Parties on climate-related issues. This ideological divide has created significant barriers to enacting substantial climate policies. However, this same gridlock may provide a form of stability for markets, particularly for GHG-intensive firms, by reducing the likelihood of sudden regulatory shifts. Consistent with this idea, Faccini, Matin, and Skiadopoulos (2023) use news coverage of U.S. climate policy to measure transition risk—defined as the financial and economic risks associated with potential policy changes aimed at reducing greenhouse gas emissions, such as carbon pricing, emissions trading schemes, or stricter environmental

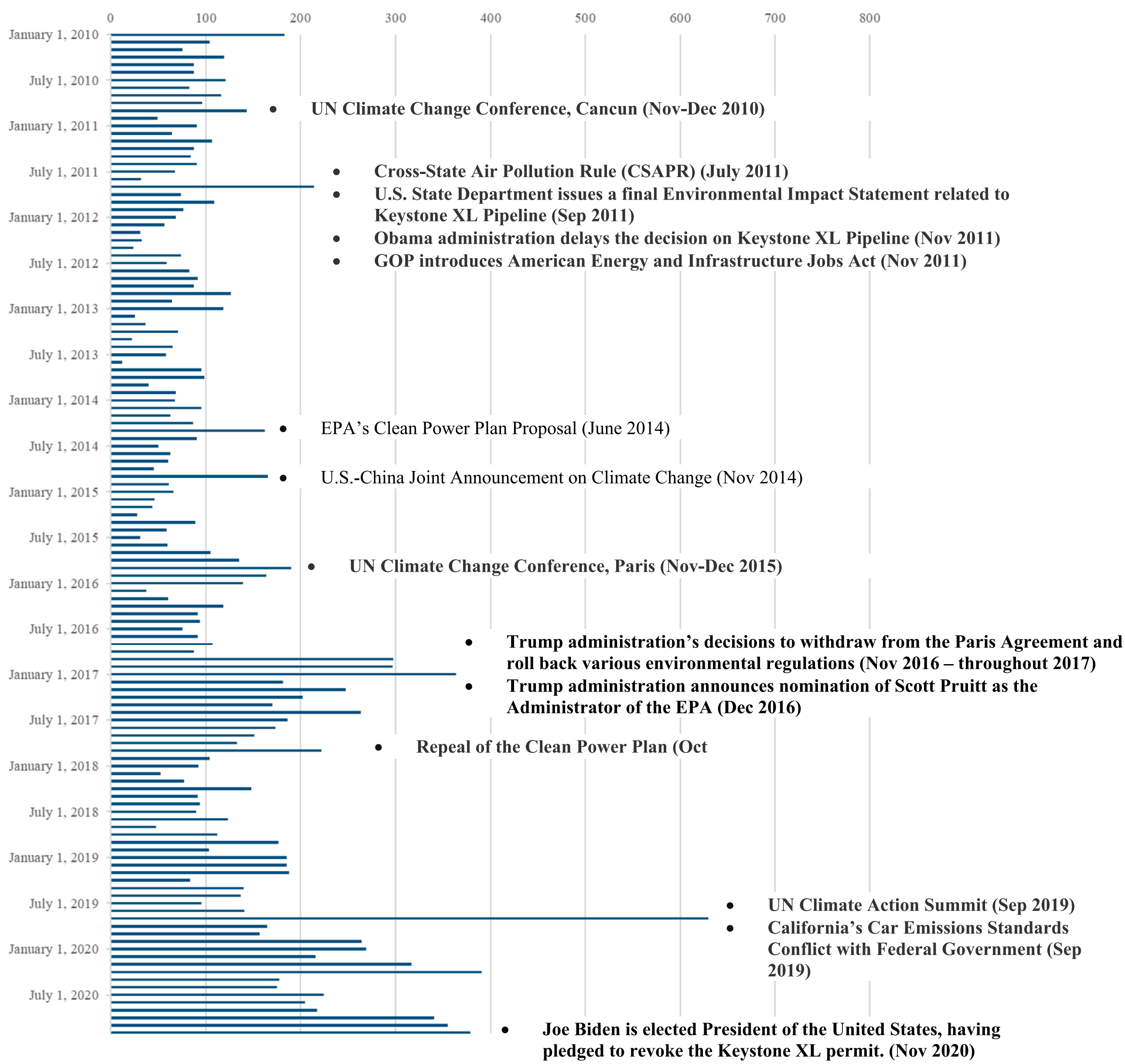

Fig. 1. Climate Policy Uncertainty Index 2010–2020.
Note to Fig. 1**:** This figure presents annotated climate policy uncertainty index charted from 2010 to 2020. Data is obtained from Gavriilidis (2021) (http://www.policyuncertainty.com).

standards. The authors observe that transition risk, which is at the heart of climate policy uncertainty, was notably reduced during both Former President Obama's second term and the Trump administration, periods marked by significant political gridlock.

Building on this literature, we propose that political gridlock fosters a stable policy environment for financial analysts, which in turn mitigates the adverse effects of CPU on their forecast quality. In a gridlocked political environment, where legislative paralysis prevents the passage of new and potentially disruptive regulations, the regulatory landscape becomes more predictable for firms, especially those in GHG-intensive industries. This predictability reduces the uncertainty analysts face when forecasting a firm's future performance, as they can rely on a more consistent set of regulations governing the firm's operations. By minimizing the risk of sudden policy shifts, political gridlock enables analysts to focus more on the fundamental aspects of the firms they cover, leading to more accurate and less varied forecasts.

2.3.2. *Financial reporting disclosure quality*

The literature in corporate finance and accounting consistently shows that a firm's financial disclosure quality is crucial in enhancing market participants' confidence in interpreting how macroeconomic news affects firm fundamentals. For instance, Armstrong, Glaeser, and Kepler (2019) demonstrate that during periods of macroeconomic shifts, such as changes in monetary policy, high-quality accounting disclosures enables more consistent market interpretation of macroeconomic news, thereby stabilizing firm valuations. Similarly, Tessema and Rubbaniy (2023) find that enhanced accounting transparency through mandatory disclosures on derivatives and hedging enables investors to better assess the underlying fundamental volatility of firms in response to interest rate changes. Additionally, Wang, Mbanyele, and Muchenje (2022) observe that increased firm-level disclosure mitigates the impact of heightened economic policy uncertainty on stock liquidity, with this effect being more pronounced for difficult-to-value securities characterized by higher information asymmetry.

We apply the above insight to the context of climate policy and propose that a firm's accounting disclosure quality can influence the impact of CPU on the quality of analyst forecasts. Specifically, when firms provide more comprehensive and transparent disclosures, analysts are better equipped to assess operational vulnerabilities and identify areas of competitive advantage in a shifting regulatory environment (e.g., Ben-Amar & McIlkenny, 2015; Bernardi & Stark, 2018a, 2018b; Liu, Bernardi, & Stark, 2024). This level of detailed disclosure also enables analysts to filter out the noise associated with climate policy development, providing clearer understanding of the firm's intrinsic strengths and long-term sustainable profitability under various policy scenarios. Consequently, we hypothesize that higher quality accounting disclosures mitigate the negative impact of CPU on financial analyst forecast quality.

2.3.3. *Financial analyst forecast expertise*

Our final hypothesis examines how financial analysts' understanding of macroeconomic factors can mitigate the impact of CPU on forecast quality. Extensive literature consistently shows that analysts' expertise significantly enhances forecast quality, especially when the forecasting task is complex. This expertise is often measured by analysts' experience, as more experienced analysts typically produce more accurate and consistent forecasts due to their deeper understanding of the firms and industries they cover. For instance, research has demonstrated that firm-specific knowledge is positively correlated with forecast accuracy (Clement, 1999; Mikhail, Walther, & Willis, 1999) and inversely related to forecast dispersion among analysts (Liu & Natarajan, 2012).

Analysts' familiarity with specific industrial sectors and their understanding of the macroeconomic factors influencing those sectors also contribute to improved forecast quality. Studies by Bradley, Gokkaya, Liu, and Xie (2017) and Dai et al. (2024) find a positive association between analysts' industrial experience and forecast accuracy. Additionally, Hugon, Kumar, and Lin (2016) observe that analysts with access to active in-house economists are more adept at incorporating negative macroeconomic news into their forecasts. This benefit is particularly significant when a firm's performance is closely tied to changes in macroeconomic conditions.

Based on these findings, we suggest that analysts who have access to comprehensive economic data and resources and are more skilled in interpreting macroeconomic trends, are better positioned to anticipate the potential impacts of climate policy uncertainty on economic conditions. Additionally, these analysts are more capable of assessing how various policy scenarios might influence the performance and strategic decisions of firms, especially those in sectors most vulnerable to such changes.

In summary, we hypothesize that political gridlock, higher-quality financial disclosures, and greater analyst forecast expertise mitigate the impact of climate policy uncertainty on the quality of financial analyst forecasts. Specifically,

HYPOTHESIS 2a. Political Gridlock mitigates the impact of climate policy uncertainty on financial analyst forecast quality

HYPOTHESIS 2b. Financial accounting disclosure quality mitigates the impact of climate policy uncertainty on the quality of financial analyst forecasts.

HYPOTHESIS 2c. Financial analysts' expertise mitigates the impact of climate policy uncertainty on the quality of financial analyst forecasts.

3. Research methods

3.1. *Climate policy uncertainty measurement*

We utilize Gavriilidis (2021) monthly CPU index (CPU^m) to evaluate variations in climate policy uncertainty over our sample period. CPU^m is compiled through monthly text searches across eight major U.S. newspapers, including the Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today, and the Wall Street Journal. To ensure newspaper articles pertains to climate policy uncertainty, the content of the articles must include three sets of keywords: (1) "*uncertain*" or "*uncertainty*"; (2) climate-related bigram, including: "*carbon dioxide*", "*climate*", "*climate risk*", "*greenhouse gas emissions*", "*greenhouse*", "*CO2*", "*emissions*", "*global warming*", "*climate change*", "*green energy*", "*renewable energy*", or "*environment*"; and (3) legislation related bigrams, including: "*regulation*", "*legislation*", "*White House*", "*Congress*", "*EPA*", "*law*", or "*policy*".[4] To account for variation in news coverage over time, Gavriilidis (2021) normalizes the raw counts by the total number of news articles across all publications for each month.

The resulting CPU^m values, reflecting the level of policy uncertainty related to climate change, are shown in Fig. 1 for the period between 2010 and 2020. This figure demonstrates clear spikes in CPU^m during periods of heightened climate-related legislative activities. Notable examples include the political conflict and policy reversal surrounding the Keystone XL Pipeline project in 2011 and 2020, the introduction and repeal of the Clean Power Plan in 2014 and 2017, the Trump administration's decision to withdraw from the Paris Agreement and roll back multiple environmental regulations between 2016 and 2017, and the conflicts between California and the federal government over environmental policies and greenhouse gas emission standards for automobiles

[4] Faccini et al. (2023) use a similar NLP algorithm to construct a monthly climate policy risk index. The main differences from Gavriilidis are in keyword scope and the number of newspaper outlets considered. To test the sensitivity of our results, we repeated the analysis using Faccini et al.'s index and found our findings remained consistent. See Section 5.2 for details on this robustness check.

in 2019.

The use of the CPU^m as a proxy for climate policy uncertainty offers distinct advantages. Firstly, the index effectively captures the ongoing and dynamic nature of the legislative process, which involves not just one, but multiple branches of government. This ongoing process often spans several election cycles, reflecting the evolving political landscape and the long-term nature of policy development. Even after specific climate policies are enacted, the index continues to capture the uncertainty that persists as these policies are implemented and potentially modified. Moreover, the CPU^m is versatile in that it accounts for uncertainty surrounding both enacted legislation and policy proposals that may never become formal laws. This flexibility ensures that the index is sensitive to the entire spectrum of policy-related uncertainty, including the risks and uncertainties associated with policies that are merely proposed or discussed but not yet formalized. This comprehensive approach allows for a more accurate reflection of the true uncertainty faced by market participants and other stakeholders.[5]

Although Gavriilidis's CPU index has empirical appeal, its robustness has not been fully established in the literature, potentially leading to measurement errors in our analysis. Given that climate policies often rely on economic mechanisms, one might argue that climate-related uncertainty may overlap with broader economic policy uncertainty.[6] To address this concern, we employ regression analyses to examine whether and how CPU index varies with climate-related legislative activities versus those unrelated to climate policies, while controlling for the general economic policy uncertainty. Specifically, we estimate the following two regression models[7]:

$$CPU_m = a_0 + a_1 BILL_m^{Climate} + a_2 BILL_m^{Fiscal} + a_3 BILL_m^{Health} + a_4 BILL_m^{Monetary} + a_5 BILL_m^{Security} + a_6 BILL_m^{Trade} + a_7 EPU_m$$

[1a]

$$CPU_m = b_0 + b_1 HEAR_m^{Climate} + b_2 HEAR_m^{Fiscal} + b_3 HEAR_m^{Health} + b_4 HEAR_m^{Monetary} + b_5 HEAR_m^{Security} + b_6 HEAR_m^{Trade} + b_7 EPU_m$$

[1b]

where CPU_m is the natural logarithm of monthly climate policy uncertainty index (Gavriilidis, 2021) for the period starting from January 2000 (the earliest available data) to December 2022. We construct two climate-related legislative variables: $BILL_m^{Climate}$ represents the percentage of bills introduced in the House of Representatives with titles matching Gavriilidis's (2021) climate policy keywords. $HEAR_m^{Climate}$ represents the percentage of congressional public hearings with titles aligned with these same keywords. If uncertainty about climate policy increases during periods of heightened legislative activity, we expect positive coefficients on $BILL_m^{Climate}$ and $HEAR_m^{Climate}$ ($a_1 > 0$; $b_1 > 0$).

To control for other legislative activities, we include non-climate-related bill introductions in eq. [1a] and non-climate-related congressional public hearings in eq. [1b]. Non-climate-related bill introduction is represented by the percentage of bills whose titles match keywords from Baker et al. (2016) across various policy domains: fiscal policy and government spending ($BILL_m^{Fiscal}$), healthcare policy ($BILL_m^{Health}$), monetary policy ($BILL_m^{Monetary}$), international trade ($BILL_m^{Trade}$), and national security ($BILL_m^{Security}$). Similarly, non-climate-related congressional public hearings are represented by the percentage of public hearings whose titles correspond to keywords from Baker et al. (2016) for the same policy domains: fiscal policy and government spending ($HEAR_m^{Fiscal}$), healthcare policy ($HEAR_m^{Health}$), monetary policy ($HEAR_m^{Monetary}$), international trade ($HEAR_m^{Trade}$), and national security ($HEAR_m^{Security}$). Finally, in both eq. [1a] and [1b], we include EPU_m, the natural logarithms of the monthly general economic policy uncertainty index (Baker et al., 2016).

Panel A of Table 1 reports the results of the regression analysis on eq. [1a]. Columns (1) and (2) indicate that the coefficients on $BILL_m^{Climate}$ are all positive and significant ($p < 0.01$), whereas the coefficients on non-climate-related bill introduction variables are not significantly different from zero. In both columns, the coefficients on EPU_m is positive and significant ($P < 0.01$), underscoring the intricate connection between climate policies and general economic policies. Nevertheless, even after controlling for general economic policy uncertainty, the relationship between climate policy uncertainty and the introduction of climate-related bills remains robust.

Panel B reports the results of the regression analysis on eq. [1b]. Consistent with Panel A, columns (1) and (2) show positive and significant ($p < 0.01$) coefficients for $HEAR_m^{Climate}$. In contrast, coefficients for non-climate-related public hearings are generally insignificant, except for $HEAR_m^{Security}$. This exception is somewhat expected given the Department of Homeland Security's role in "*formulating and enforcing policies aimed at promoting national preparedness, resilience, and adaptation to severe climate changes*" (U.S. Department of Homeland Security, 2024). Similar to the findings in Panel A, to control for general economic policy uncertainty does not reduce the significance of the relationship between climate policy uncertainty and climate-related public hearings.

Collectively, the findings from the analyses confirm that the CPU index significantly correlates with actual climate-related legislative activities, distinguishing itself from uncertainties associated with other specific policies and general economic policy. Therefore, we conclude that the CPU index is a suitable measure for our hypothesis testing (discussed further below).

3.2. Sample selection and sample distribution

Panel A of Table 2 outlines the sample selection process for our analysis of how climate policy uncertainty affects financial analyst forecasts. We focus on firms classified as GHG-intensive according to the U.S. EPA Greenhouse Gas Reporting Program (GHGRP), codified at 40 CFR Part 98 in 2010. The GHGRP mandates that facilities report greenhouse gas (GHG) data if: (1) GHG emissions from covered sources exceed 25,000 metric tons CO2e per year; (2) supply of certain products would result in over 25,000 metric tons CO2e of GHG emissions if those products were released, combusted, or oxidized; or (3) the facility receives 25,000 metric tons or more of CO2 for underground injection. Approximately 7600 direct-emitting facilities report their emissions annually, accounting for about 50 % of total U.S. GHG emissions. The data reported covers 85 %–90 % of U.S. GHG emissions (Environmental Protection Agency, 2022). We hand-matched GHGRP-reported facilities with COMPUSTAT firms to form our initial sample, consisting of 3763 firm-year observations for 482 distinct firms. We then excluded observations missing sufficient data from the I/B/E/S database to calculate analyst forecast quality. We further eliminate observations without sufficient data to calculate firm-specific control variables. Accordingly,

[5] Gavriilidis's (2021) index has recently gained popularity as a tool for measuring climate policy uncertainty. Guesmi, Makrychoriti, and Spyrou (2023) find that natural disasters drive climate policy uncertainty, as measured by this index. Karlilar Pata and Balcilar (2024) show that uncertainty surrounding climate policy, as captured by the Gavriilidis index, is leading to a shift in the U.S. energy composition, with a growing focus on renewable energies. Bouri, Iqbal, and Klein (2022) use the Gavriilidis index to provide empirical evidence that climate policy uncertainty significantly affects the performance of green energy stocks relative to brown energy stocks. Furthermore, Ghani, Zhu, Qin, and Ghani (2024) demonstrate that the Gavriilidis index is useful for forecasting U.S. stock market volatility.

[6] For example, the Energy Innovation and Carbon Dividend Act of 2023 (H.R.5744) introduces carbon fees on fossil fuel emissions to incentivize a shift to carbon-free production and supply chains, aiming to help the U.S. achieve carbon neutrality by 2050. Another example is the Build Back Better Act, proposed by the White House in 2022, which included subsidies for renewable energy projects, electric vehicle infrastructure, and energy-efficient home improvements to promote clean energy and climate resilience.

[7] See Appendix 1 for detail variable definition.

Table 1
Relationship between Climate Policy Uncertainty on Legislative Activities

Panel A: Legislative Activities proxied by Number of Bills First Introduced by the House of Representatives

	Dependent Variable = CPU_m	
Explanatory Variables	(1)	(2)
$BILL_m^{Climate}$	52.0584***	50.7147***
	(6.18)	(5.92)
$BILL_m^{Fiscal}$		−0.7191
		(−0.29)
$BILL_m^{Health}$		0.1190
		(0.03)
$BILL_m^{Monetary}$		−0.5897
		(−0.08)
$BILL_m^{Security}$		3.8835
		(0.76)
$BILL_m^{Trade}$		4.5403
		(1.65)
EPU_m	0.8359***	0.8325***
	(5.43)	(5.27)
Intercept	*Included*	*Included*
N	252	252
R^2	0.2894	0.3012
R^2_{adj}	0.2837	0.2812

Panel B: Legislative Activities proxied by Public Hearings held by Congressional Committees

	Dependent Variable = CPU_m	
Explanatory Variables	(1)	(2)
$HEAR_m^{Climate}$	12.6768***	13.3814***
	(2.97)	(3.14)
$HEAR_m^{Fiscal}$		−0.5451
		(−0.91)
$HEAR_m^{Health}$		1.5231
		(0.19)
$HEAR_m^{Monetary}$		2.0922
		(0.33)
$HEAR_m^{Security}$		4.6324**
		(2.09)
$HEAR_m^{Trade}$		9.6156
		(1.65)
EPU_m	1.1180***	1.0822***
	(7.37)	(7.07)
Intercept	*Included*	*Included*
N	252	252
R^2	0.1979	0.2240
R^2_{adj}	0.1917	0.2027

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Note to Table 1: This table reports the results for variants of the following regression models:

$$CPU_m = a_0 + a_1 BILL_m^{Climate} + a_2 BILL_m^{Fiscal} + a_3 BILL_m^{Health} + a_4 BILL_m^{Monetary} + a_5 BILL_m^{Security} + a_6 BILL_m^{Trade} + a_7 EPU_m \quad [1a]$$

$$CPU_m = b_0 + b_1 HEAR_m^{Climate} + b_2 HEAR_m^{Fiscal} + b_3 HEAR_m^{Health} + b_4 HEAR_m^{Monetary} + b_5 HEAR_m^{Security} + b_6 HEAR_m^{Trade} + b_7 EPU_{m.} \quad [1b]$$

We use ordinary least squares regression to estimate the above models and report the results in Panel A and Panel B, respectively. Variables are defined as follows: CPU_m = Natural logarithm of monthly climate policy uncertainty index. $BILL_m^{Climate}$ = Percentage of bills introduced to the House of Representatives during the month are related to climate issues. $BILL_m^{\phi}$ = Percentage of bills introduced to the House of Representatives each month are categorized into fiscal policy and government spending (ϕ = Fiscal), healthcare (ϕ = Health), monetary policy (ϕ = Monetary), national security (ϕ = Security), and international trade (ϕ = Trade). $HEAR_m^{Climate}$ = Percentage of public hearings held by congressional committees during the month are related to climate issues. $HEAR_m^{\phi}$ = Percentage of public hearings held by congressional committees each month are categorized into fiscal policy and government spending (ϕ = Fiscal), healthcare (ϕ = Health), monetary policy (ϕ = Monetary), national security (ϕ = Security), and international trade (ϕ = Trade). EPU_m = Natural logarithm of monthly economic policy uncertainty index. See the appendix for detailed variable definitions.

the final sample consists of 2025 observations for 351 distinct firms.

Panels B and C of Table 2 show the distribution of the sample by year and industry group. Panel B shows that sample observations are generally evenly distributed over the sample period from 2010 to 2020.[8,9] The industry groups in Panel C are categorized using the Three-Digit NAICS code. Unsurprisingly, the most heavily represented industry groups are utilities (19.65 %), chemical manufacturing (13.33 %), oil and gas extraction (12.74 %), computer and electronic product manufacturing (5.28 %), and food manufacturing (5.19 %), collectively accounting for more than half (56.19 %) of the sample. All other individual industry groups each contain less than 5 % of sample observations.

3.3. Testing of H1

Our first hypothesis predicts that CPU adversely affects financial analyst forecast quality, leading to increased forecast disagreement and forecast accuracy. Prior literature has shown that policy uncertainty affects economic activity and performance in the short term (Da, Engelberg, & Gao, 2014; Hassan, Hollander, van Lent, & Tahoun, 2017; Scotti, 2016) as well as in the long term (Barrero, Bloom, & Wright, 2017; Yu, Fang, Du, & Yan, 2017). Therefore, we assess both short-term and long-term analyst forecast disagreement with standard deviations of one-year-ahead earnings forecasts ($DISPAF_{y+1}$) and of long-term earnings growth rate forecasts ($DISPAF_{ltg}$), respectively. Similarly, we measure both short-term and long-term analyst forecast accuracy with the average of absolute forecast error in one-year-ahead earnings forecasts ($ABSFE_{y+1}$) and in long-term earnings growth rate forecasts ($ABSFE_{ltg}$), respectively. To mitigate potential confounding factors such as forecast staleness (Cheong & Thomas, 2011) and preliminary-earnings announcement (Clement, Frankel, & Miller, 2003; Rogers, Skinner, & Van Buskirk, 2009), we calculate forecast disagreement and forecast accuracy measurements based on analyst forecasts issued during the three-month following current annual earnings announcement.[10]

We examine the empirical relationship between CPU and analysts' forecast quality using regression models that incorporate firm-specific financial variables, macroeconomic controls, and industry fixed

[8] Our sample period ends in 2020, as we require firm-year observations to have I/B/E/S actual earnings data for the subsequent four years to measure the accuracy of analysts' forecasts for the firms' long-term earnings growth.

[9] Bilinski (2023) and Hao, Xue, Yau, and Zhang (2022) document that the COVID-19 outbreak in 2020 significantly impacted financial analysts' forecasting behavior as well as their forecast quality. To evaluate the robustness of our primary results, we repeated our analysis on equations [2a] and [2b] using a pre-2020 sample. The results and statistical inferences remain qualitatively similar in this alternative period.

[10] Our analysis relies on analysts' forecasts issued after annual earnings announcements, ensuring they have access to comprehensive, audited financial data. To test robustness, we also analyze forecasts issued after quarterly earnings announcements. The results (not shown) from this alternative approach are consistent with those reported in the paper.

effects[11]:

$$DISPAF_\tau = a_0 + a_1 CPU + a_2 AF_\tau + a_3 FLLW_\tau + a_4 SUR + a_5 ROA + a_6 OCF + a_7 ROAVOL + a_8 LOSS + a_9 M\&A + a_{10} LEV + a_{11} BTM + a_{12} INTAN + a_{13} SIZE + a_{14} BIG4 + a_{15} HHI + a_{16} EMV + a_{17} ROLLCALLS + a_{18} ELECTIONYR + a_{19} EPU + Industry\ Fixed\ Effects + \varepsilon \tag{2a}$$

$$ABSFE_\tau = b_0 + b_1 CPU + b_2 AF_\tau + b_3 FLLW_\tau + b_4 SUR + b_5 ROA + b_6 OCF + b_7 ROAVOL + b_8 LOSS + b_9 M\&A + b_{10} LEV + b_{11} BTM + b_{12} INTAN + b_{13} SIZE + b_{14} BIG4 + b_{15} HHI + b_{16} EMV + b_{17} ROLLCALLS + b_{20} ELECTIONYR + b_{19} EPU + Industry\ Fixed\ Effects + \varepsilon \tag{2b}$$

Dependent variables $DISPAF_\tau$ and $ABSFE_\tau$ represent the analyst forecast disagreement and forecast accuracy for one-year-ahead earnings ($\tau = y + 1$) and long-term earnings growth rate ($\tau = ltg$). Our primary explanatory variable is *CPU*, defined as the natural logarithm of the average value of monthly climate policy uncertainty index during the three-month period following the annual earnings announcement. If analysts' forecast quality deteriorates with increasing climate policy uncertainty, we expect positive coefficients for *CPU* in eq. [2a] and [2b] ($a_1 > 0$; $b_1 > 0$).

We include controls directly related to analyst forecast properties. AF_τ represents the average earnings forecast, with $\tau = y + 1$ indicating the one-year-ahead forecast horizon and $\tau = ltg$ indicating the long-term forecast horizon. $FLLW_\tau$ represents the number of analysts issuing forecasts during the three months following the annual earnings announcement. We expect these variables to be positively associated with forecast dispersion and inaccuracy for their respective horizons. Additionally, *SUR* is the current-year earnings surprise, which introduces information uncertainty (Francis, Lafond, Olsson, & Schipper, 2007; Liang, 2003). We expect a positive coefficient for *SUR* in our models.

We account for firms' financial performance using return on assets (*ROA*) and operating cash flows (*OCF*). We also include earnings volatility (*ROAVOL*), operating losses (*LOSS*), and merger and acquisition activities (*M&A*) that reflect less stable earnings performance (Basu, 1997; Dichev & Tang, 2009; Erickson, Wang, & Zhang, 2012; Hayn, 1995). We expect these three variables to have positive coefficients. Financial leverage (*LEV*) and the book-to-market ratio (*BTM*) are included to capture debt burden and financial distress, which are expected to be positively correlated with analyst forecast disagreement and inaccuracy (Ciccone, 2001). Although prior research suggests that intangible assets add complexity to the forecasting task, empirical findings have been mixed (Barron, Byard, Kile, & Riedl, 2002). Therefore, we control for intangible assets (*INTAN*) without predicting the direction of its coefficients. Additionally, firm size (*SIZE*) and audit quality (*BIG4*) are included to control for the quality of accounting information available to analysts (Behn, Choi, & Kang, 2008; Lang & Lundholm, 1996). These variables are expected to be negatively related to the dependent variables.

We also account for macroeconomic conditions and general legislative uncertainties, which have been shown in prior literature to impact analysts' information environment and forecast quality. The Herfindahl-Hirschman Index (*HHI*) measures product market concentration, indicating an industry's resilience to macroeconomic shocks (Datta, Iskandar-Datta, & Sharma, 2011; Haw, Hu, & Lee, 2015). Equity market volatility (*EMV*) reflects investor uncertainty in response to macroeconomic shocks, leading to greater stock price fluctuations (Chen, Roll, & Ross, 1986). We expect a negative coefficient for *HHI* and a positive coefficient for *EMV*.

To capture general legislative uncertainties, we include the number of roll-call votes in Congress (*ROLLCALLS*), an indicator for presidential election years (*ELECTYR*), and the economic policy uncertainty index (*EPU*). Since these uncertainties likely complicate analysts' forecasting tasks, we anticipate positive coefficients for these three proxies (Cheng,

[11] Firm and year subscripts are suppressed for brevity. See Appendix 1 for detailed variable definition.

Table 2
Sample Selection and Distribution

Panel A. Sample Selection

	Firm-Year Observations	Distinct Firms
Initial: Firm-years subject to Greenhouse Gas Reporting Program between 2011 (Source: www.EPA.gov) to 2020.	3763	482
Exclude: Firm-years without sufficient data to calculate disagreement among financial analysts in the firm's one-year-ahead earnings and its long-term growth rate.	(1674)	(119)
Exclude: Firm-years without sufficient data to calculate firm-specific control variables.	(64)	(12)
Final Sample	**2025**	**351**

Panel B. Sample Distribution by Year

Year	Frequency	Percentage
2010	183	9.04
2021	200	9.88
2012	191	9.43
2013	196	9.68
2014	194	9.58
2015	180	8.89
2016	172	8.49
2017	183	9.04
2018	201	9.93
2019	203	10.02
2020	122	6.02
All Years	2025	100.00

Panel C. Sample Distribution by Industry

Three-Digit NAICS Code	Industry	Frequency	Percentage
221	Utilities	398	19.65
325	Chemical Manufacturing	270	13.33
211	Oil and Gas Extraction	258	12.74
334	Computer and Electronic Product Manufacturing	107	5.28
311	Food Manufacturing	105	5.19
336	Transportation Equipment Manufacturing	99	4.89
212	Mining (except Oil and Gas)	83	4.10
324	Petroleum and Coal Products Manufacturing	78	3.85
333	Machinery Manufacturing	76	3.75
486	Pipeline Transportation	67	3.31
312	Beverage and Tobacco Product Manufacturing	62	3.06
327	Nonmetallic Mineral Product Manufacturing	57	2.81
562	Waste Management and Remediation Services	41	2.02
424	Merchant Wholesalers, Nondurable Goods	39	1.93
	Other Industries	229	11.33
	All Industries	**2025**	**100.00**

Note to Table 2: Panel A of this table summarizes the sample selection process. Panels B and C report the sample distribution by year and by Three-Digit NAICS code industry classification (www.census.gov/naics/), respectively.

2022; Chourou et al., 2021; Goodell, McGee, & McGroarty, 2020; Li & Born, 2006; Nagar et al., 2019).

3.4. Testing of H2a – H2c

H2a explores the impact of political gridlock on the relationship between CPU and analyst forecast quality. Political gridlock occurs when opposing parties or factions have little common ground and prioritize obstructing each other's agendas, leading to legislative stalemate or paralysis. In our study, we expect that such gridlock may delay the development of new climate policies, thereby reducing uncertainty about potential policy changes and diminishing their impact on analyst forecast quality. As a result, we posit that the relationship between CPU and analyst forecast quality weakens in the presence of political gridlock.

Political science literature suggests that the threat of political gridlock is most evident when there is a *combination* of split party control of government and polarized ideology between parties (Binder, 1999; Fiorina & Abrams, 2008; McCarty & Razaghian, 1999). Given the bicameral structure of Congress, we operationalize political gridlock (*GRIDLOCK*) as follows:

$$\sum_{c} DIV_c \times POLAR_c \tag{3}$$

where DIV_c is an indicator variable that equals to 1 if the majority political party in the House ($c = House$) and the Senate ($c = Senate$), respectively, is different from the president's party affiliation. $POLAR_c$ represents the party polarization in the House ($c = House$) and the Senate ($c = Senate$), respectively. Party polarization in each chamber is calculated as the difference in the average political ideology scores between Democrats and Republicans. These scores are based on the political ideology spectrum developed by Poole and Rosenthal (2000), who use dynamic weighted nominal three-step estimation to map each Congress member's roll-call voting records onto a liberal-conservative spectrum ranging from −1 (extremely liberal) to +1 (extremely conservative).[12]

To test H2a, we estimate the following models along with the same sets of controls employed in eq. [2a] and [2b]:

$$DISPAF_\tau = a_0 + a_1 CPU^d + a_2 GRIDLOCK + a_3 CPU^d \times GRIDLOCK + Control\ Variables + \varepsilon \tag{4a}$$

$$ABSFE_\tau = b_0 + b_1 CPU^d + b_2 GRIDLOCK + b_3 CPU^d \times GRIDLOCK + Control\ Variables + \varepsilon \tag{4b}$$

For ease of interpretation, we transform climate policy uncertainty into an indicator variable (CPU^d) that identifies periods of high uncertainty regarding climate policy. This transformation allows us to compare times of high versus low climate policy uncertainty and evaluate the impact of political gridlock during these periods. Since political gridlock may lead to legislative stalemates, reducing the impact of uncertainty about future climate policies on analyst forecast quality, we expect the coefficients for the interaction between, we expect the coefficients for interaction of CPU^d and *GRIDLOCK* in eqs. [4a] and [4b] to be negative ($a_3 < 0$; $b_3 < 0$).

H2b explores the impact of financial reporting disclosure quality on the hypothesized relationship between climate policy uncertainty and analyst forecast quality. To test this hypothesis, we estimate the following models:

$$DISPAF_\tau = a_0 + a_1 CPU^d + a_2 FRDQ_\theta + a_3 CPU^d \times FRDQ_\theta + Control\ Variables + \varepsilon \tag{5a}$$

$$ABSFE_\tau = b_0 + b_1 CPU^d + b_2 FRDQ_\theta + b_3 CPU^d \times FRDQ_\theta + Control\ Variables + \varepsilon \tag{5b}$$

where financial reporting disclosure quality ($FRDQ_\theta$), measured in two ways: (1) as an indicator of a low absolute discretionary accruals ($\theta = abacc$), estimated using financial accounting information at earnings announcement date (Dechow, Richardson, & Tuna, 2003); (2) as a disclosure quality score ($\theta = score$), derived from the first principal component score estimated based on the number of analysts following, analyst forecast accuracy, bid-ask spread, and trading volume during the nine-month period leading up to the fiscal year-end (Baik, Brockman, Farber, & Lee, 2018). While both measures characterize the firm's disclosure quality, they differ in focus: $FRDQ_{abacc}$ relates to the persistence of earnings and accounting accruals, whereas $FRDQ_{score}$ captures reduced information asymmetry among financial analysts due to enhanced formal and informal communication from the firms, such as through earnings calls, press releases, analyst meetings, and public information flows. Given that high financial reporting disclosure quality may mitigate the adverse effects of macroeconomic factors, particularly climate policy uncertainty, on analysts' information environment, we expect the coefficients on interaction term between CPU^d and $FRDQ_\theta$in eqs. [5a] and [5b] to be negative ($a_3 < 0$; $b_3 < 0$).

Finally, we test H2c by examining whether analysts' expertise moderates the impact of climate policy uncertainty on their forecast quality with the following models:

$$DISPAF_\tau = a_0 + a_1 CPU^d + a_2 EXPRT_\lambda + a_3 CPU^d \times EXPRT_\lambda + Control\ Variables + \varepsilon \tag{6a}$$

$$ABSFE_\tau = b_0 + b_1 CPU^d + b_2 EXPRT_\lambda + b_3 CPU^d \times EXPRT_\lambda + Control\ Variables + \varepsilon \tag{6b}$$

The main variable of interest is analysts' expertise ($EXPRT_\lambda$). Although this construct is difficult to measure directly, prior research suggests that macroeconomic expertise can be inferred from analysts' industry experience and their affiliation with larger brokerage firms. Thus, we measure analysts' expertise ($EXPRT_\lambda$) in two ways: (1) as an indicator of industry specialization ($\lambda = ind\,exp$), equal to 1 if the average industry experience of analysts issuing forecasts is in the highest quintile of the sample distribution; and (2) as an indicator of large brokerage affiliation ($\lambda = large\ broker$), equal to 1 if more than half of the analysts issuing forecasts are employed by large brokerage houses. Large brokerage houses are defined as the top five firms employing the most analysts in the six months leading up to the current annual earnings announcement. Since expertise may enable analysts to better understand factors affecting firms' fundamentals in uncertain macroeconomic environments, we expect the coefficients on interaction term between CPU^d and $EXPRT_\lambda$ in eqs. [6a] and [6b] to be negative ($a_3 < 0$; $b_3 < 0$).

4. Empirical results

4.1. Summary statistics

Table 3 provides summary statistics for the variables used in our regression analyses. The primary independent variable, *CPU*, representing climate policy uncertainty, has a mean of 4.6017, with significant variation ranging from 62.8000 at the 25th percentile to 162.6475 at the 75th percentile, reflecting considerable fluctuation over the sample period. The mean (median) values for one-year-ahead earnings forecast dispersion ($DISP_{y+1}$) and absolute forecast error ($ABSFE_{y+1}$) are 0.0090 and 0.0169 (0.0039 and 0.0073), respectively. In contrast, the

[12] Poole and Rosenthal's (2000) measurement is widely used in political science literature to illustrate the increasing ideological divide between the Democratic and Republican parties, as both have become more ideologically homogeneous and cohesive (e.g., Barber, McCarty, Mansbridge, & Martin, 2015; Clinton, Jackman, & Rivers, 2004; Farina, 2015; McCarty, Poole, and Rosenthal, 2006).

Table 3
Summary Statistics.

Variable	Mean	25th PCTL.	50th PCTL.	75th PCTL.	Std. Dev.
Main variables of interest:					
CPU	4.6017	4.1400	4.5265	5.0916	0.6275
CPU *(raw value)*	121.2710	62.8000	92.4300	162.6475	77.7884
$DISPAF_{y+1}$	0.0090	0.0015	0.0039	0.0096	0.0157
$DISPAF_{ltg}$	0.3657	0.0264	0.0728	0.2163	1.3037
$ABSFE_{y+1}$	0.0169	0.0032	0.0073	0.0170	0.0296
$ABSFE_{ltg}$	0.7634	0.0639	0.2040	0.5795	2.1782
Analyst-related control variables:					
AF_{y+1}	0.0616	0.0477	0.0601	0.0770	0.0386
AF_{ltg}	0.4335	0.0676	0.1507	0.3509	1.6743
$FLLW_{y+1}$	2.6549	2.3026	2.7081	2.9957	0.4982
$FLLW_{ltg}$	1.4175	1.0986	1.3863	1.6094	0.3044
$FLLW_{y}$	2.2553	1.7918	2.3979	2.8332	0.6965
SUR	0.0045	0.0005	0.0016	0.0043	0.0112
Firm-specific control variables:					
ROA	0.0545	0.0253	0.0447	0.0823	0.0613
OCF	0.0987	0.0654	0.0886	0.1240	0.0529
ROAVOL	0.0099	0.0035	0.0060	0.0109	0.0128
LOSS	0.0341	0.0000	0.0000	0.0000	0.1816
M&A	0.1054	0.0000	0.0000	0.0000	0.3071
LEV	1.3850	0.5670	0.9189	1.3662	4.0980
BTM	0.5038	0.2854	0.4493	0.6404	0.3305
INTAN	0.1686	0.0134	0.1017	0.2801	0.1817
SIZE	9.2012	8.0863	9.1234	10.1917	1.4681
BIG4	0.9683	1.0000	1.0000	1.0000	0.1752
Macroeconomic and policy-related control variables:					
HHI	0.0723	0.0169	0.0493	0.0947	0.0861
EMV	1.3272	1.1058	1.2865	1.4257	0.3433
ROLLCALLS	7.4736	7.0229	7.7213	8.1409	0.8957
ELECTYR	0.1806	0.0000	0.0000	0.0000	0.3848
EPU	4.8648	4.6660	4.7851	5.0141	0.2723

Note to Table 3: This table presents summary statistics for the variables used in the regression analyses. Variables are defined as follows: ***CPU*** = Natural logarithm of the average Climate Policy Uncertainty index value during the 3-month period following the annual earnings announcement. $DISPAF_{\tau}$ = Analyst forecast dispersion for one-year ahead earnings ($\tau = y+1$) or long-term earnings growth rate ($\tau = ltg$). $ABSFE_{\tau}$ = Absolute error in analyst forecasts for one-year ahead earnings ($\tau = y+1$), or long-term earnings growth rate ($\tau = ltg$). AF_{τ} = Analyst forecast for one-year-ahead earnings ($\tau = y+1$) or long-term earnings growth rate ($\tau = ltg$). $FLLW_{\tau}$ = Number of analysts covering the firms' current-year earnings ($\tau = y$), one-year-ahead earnings ($\tau = y+1$), or long-term earnings growth rate ($\tau = ltg$). ***SUR*** = Earnings surprise. ***ROA*** = Return on assets. ***OCF*** = Cash flows from operating activities. ***ROAVOL*** = Volatility of quarterly return on assets over the previous 8 quarters. ***LOSS*** = Operating loss indicator. ***M&A*** = Merger and acquisition indicator. ***LEV*** = Financial leverage. ***BTM*** = Book-to-market ratio. ***INTAN*** = Intangible assets. ***SIZE*** = Firm size. ***BIG4*** = Audited by big-four CPA firms. ***HHI*** = Herfindahl-Hirschman Index. ***EMV*** = Natural logarithm of the average Equity Market Volatility index value during the 3-month period following the annual earnings announcement. ***ROLLCALSS*** = Natural logarithm of the number of roll-call voting in Congress during the 3-month period following the annual earnings announcement. ***ELECTYR*** = Indicator of whether annual earnings announcement occurs during presidential election year. ***EPU*** = Natural logarithm of the average Economic Policy Uncertainty index value during the 3-month period following the annual earnings announcement. See the appendix for detailed variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles.

mean (median) values for long-term earnings growth forecast dispersion ($DISP_{ltg}$) and absolute forecast error ($ABSFE_{ltg}$) are 0.3657 and 0.7634 (0.07028 and 0.2040), respectively. As expected, both forecast dispersion and absolute forecast error increase with the length of the forecast horizon.

Table 4 presents the Pearson correlation coefficients for the variables reported in Table 3. The primary purpose of this table is to identify any harmful collinearity among the regressors in the subsequent regression analyses. No correlation coefficient among the independent variables exceeds 0.50, indicating that multicollinearity is not a significant issue in our data.[13]

4.2. Results on climate policy uncertainty and analyst forecast quality

Table 5 presents the results of our first hypothesis, testing the relationship between CPU and analyst forecast quality, measured by forecast dispersion and absolute forecast error. Columns (1) and (2) evaluate the impact of climate policy uncertainty on forecast dispersion for one-year-ahead earnings and long-term earnings growth using eq. [2a], with positive and significant coefficients for *CPU* ($p < 0.05$) in both cases. Similarly, columns (3) and (4) examine the effect of climate policy uncertainty on absolute forecast error for one-year-ahead earnings and long-term earnings growth using eq. [2b], also showing positive and significant *CPU* coefficients ($p < 0.05$). Moreover, the coefficient for *CPU* is statistically smaller in column (1) than in column (2) (*Z*-statistic = 2.15; $p < 0.05$), and similarly, smaller in column (3) than in column (4) (Z-statistic = 3.12; $p < 0.01$).[14]

Taken together, these findings support our hypothesis that climate policy uncertainty deteriorates analyst forecast quality, leading to increased forecast dispersion and reduced forecast accuracy. The results also suggest that climate policy uncertainty affects analysts' forecasts of both short- and long-horizon earnings, with a more pronounced impact on long-term forecasts. In terms of economic significance, an increase in CPU from the first quartile to the third quartile (0.8796 = 5.0916–4.1400) would lead to an increase in $DISPAF_{y+1}$ and $DISPAF_{ltg}$ by 0.0026 (= 0.8796 × 0.0030) and 0.0023 (= 0.8796 × 0.0026), respectively, representing 29.32 % and 31.26 % of the average values of the respective forecast dispersion measures. Similarly, the same increase in CPU would result in an increase in $ABSFE_{y+1}$ and $ABSFE_{ltg}$ by 0.0023 (= 0.8796 × 0.0026) and 0.1833 (= 0.8796 × 0.2084), respectively, representing 13.53 % and 24.01 % of the average values of the respective absolute forecast error measures.[15]

The results for the control variables are generally consistent with our expectations. Among firm-specific controls, the coefficients on *SUR* are positive and significant, except in column (2). The coefficients on *ROAVOL* and *INTAN* are consistently positive, while the coefficient on *SIZE* is consistently negative, though with varying levels of statistical significance. Regarding macroeconomic conditions and general legislative uncertainty controls, the coefficients on the equity investor uncertainty index (*EMV*) are positive and generally significant. As anticipated, the coefficients on *EPU* are positive and significant for short-horizon earnings forecasts (columns (1) and (3)) but become insignificant for

[13] To provide further assurance that are not susceptible to collinearity among the independent variables, we perform an analysis of variance inflation factors (VIF) on equations [2a] and [2b]. Unreported result suggests that multicollinearity is not an issue, as all VIF for each independent variable are below 10.

[14] We assess the impact of *CPU* on non-GHG-intensive firms (i.e., those not subject to GHGRP) by reanalyzing equations [2a] and [2b] for this group. As expected, the results (not shown) indicate that CPU has a stronger effect on GHG-intensive firms than on non-GHG-intensive firms. This analysis further highlights that CPU represents climate-specific uncertainty, with a greater impact on firms more vulnerable to abrupt climate policy changes.

[15] For comparison, an increase in *EPU* from the first quartile to the third quartile (0.3481 = 5.0141–4.6660) would result in an increase in $DISPAF_{y+1}$ and $ABSFE_{y+1}$ by 0.0015 (= 0.3481 × 0.0042) and 0.0026 (= 0.3481 × 0.0074), respectively. These changes represent 16.24 % and 15.38 % of the average values of dispersion and absolute error in one-year-ahead analyst earnings forecasts, respectively. This suggests that *CPU* has a greater impact on analyst forecast quality than EPU among greenhouse gas -intensive firms.

Table 4
Pearson Correlation Matrix.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
CPU	**(1)**	1.00												
$DISPAF_{y+1}$	**(2)**	0.12***	1.00											
$DISPAF_{ltg}$	**(3)**	0.05**	0.44***	1.00										
$ABSFE_{y+1}$	**(4)**	0.05**	0.78***	0.42***	1.00									
$ABSFE_{ltg}$	**(5)**	−0.01	0.52***	0.65***	0.53***	1.00								
AF_{y+1}	**(6)**	−0.09***	−0.27***	−0.20***	−0.25***	−0.25***	1.00							
AF_{ltg}	**(7)**	−0.07***	−0.01	0.09***	0.02	0.40***	0.02	1.00						
$FLLW_{y+1}$	**(8)**	0.03	0.08***	0.06**	0.10***	−0.01	−0.09***	−0.06**	1.00					
$FLLW_{ltg}$	**(9)**	0.02	−0.04*	−0.05**	−0.04**	−0.11***	0.05**	−0.07***	0.36***	1.00				
$FLLW_{y}$	**(10)**	0.01	0.11***	0.06***	0.12***	0.03	−0.04*	−0.02	0.70***	0.19***	1.00			
SUR	**(11)**	−0.04*	0.43***	0.15***	0.47***	0.27***	−0.07***	0.10***	−0.04*	−0.07***	0.01	1.00		
ROA	**(12)**	−0.04**	−0.11***	−0.12***	−0.11***	−0.13***	0.29***	−0.11***	0.13***	0.06**	0.08***	−0.11***	1.00	
OCF	**(13)**	−0.00	0.05**	−0.03	0.06***	−0.03	0.11***	−0.10***	0.27***	0.09***	0.19***	−0.05**	0.72***	1.00
ROAVOL	**(14)**	−0.05**	0.26***	0.19***	0.29***	0.20***	−0.11***	0.12***	0.09***	−0.07***	0.12***	0.13***	−0.09***	0.21***
LOSS	**(15)**	0.01	0.22***	0.15***	0.27***	0.18***	−0.33***	0.10***	0.16***	−0.03	0.13***	0.14***	−0.37***	−0.04*
M&A	**(16)**	−0.03	−0.02	−0.01	−0.02	0.02	0.01	0.03	0.01	−0.02	0.01	0.03	−0.03	−0.05**
LEV	**(17)**	0.16***	−0.23***	−0.14***	−0.21***	−0.16***	0.04*	−0.07***	0.13***	0.13***	0.05**	−0.13***	0.13***	−0.03
BTM	**(19)**	−0.00	0.01	0.00	0.07***	−0.01	0.05**	0.01	0.01	0.00	−0.01	0.07***	−0.04*	−0.09***
INTAN	**(18)**	−0.04*	0.53***	0.33***	0.44***	0.39***	−0.17***	−0.01	−0.04**	−0.10***	−0.00	0.26***	−0.35***	−0.22***
SIZE	**(20)**	0.16***	−0.26***	−0.19***	−0.25***	−0.30***	0.07***	−0.18***	0.57***	0.43***	0.41***	−0.21***	0.14***	0.10***
BIG4	**(21)**	0.02	−0.09***	−0.04*	−0.08***	−0.10***	0.07***	−0.08***	−0.04*	0.04	−0.05**	−0.07***	0.03	−0.06***
HHI	**(22)**	0.00	0.04*	0.01	0.03	0.01	−0.01	0.01	0.05**	−0.05**	0.02	0.01	0.07***	0.03
EMV	**(23)**	0.11***	0.22***	0.11***	0.10***	0.06***	−0.07***	−0.07***	−0.01	−0.02	0.01	−0.00	0.04	0.03
ROLLCALLS	**(24)**	−0.23***	0.03	−0.01	0.03	0.01	0.01	0.00	0.01	0.05**	0.03	0.04*	−0.05**	−0.05**
ELECTYR	**(25)**	−0.29***	−0.03	−0.03	0.02	0.01	−0.01	0.01	−0.03	−0.06**	−0.01	−0.03	0.04*	0.02
EPU	**(26)**	0.47***	0.21***	0.11***	0.11***	0.04*	−0.03	−0.08***	−0.03	−0.03	−0.03	−0.02	0.02	0.01

		(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
ROAVOL	**(14)**	1.00												
LOSS	**(15)**	0.42***	1.00											
M&A	**(16)**	0.02	−0.04*	1.00										
LEV	**(17)**	−0.19***	−0.11***	0.17***	1.00									
BTM	**(19)**	−0.02	−0.00	0.00	0.01	1.00								
INTAN	**(18)**	0.10***	0.18***	−0.03	−0.26***	−0.13***	1.00							
SIZE	**(20)**	−0.23***	−0.09***	−0.02	0.29***	0.02	−0.34***	1.00						
BIG4	**(21)**	−0.17***	−0.11***	0.02	0.10***	0.03	−0.05**	0.16***	1.00					
HHI	**(22)**	0.02	−0.02	−0.02	0.09***	0.04	−0.07***	0.02	−0.02	1.00				
EMV	**(23)**	−0.01	−0.05**	−0.03	−0.05**	0.02	0.06***	−0.01	0.00	0.04**	1.00			
ROLLCALLS	**(24)**	0.02	0.04*	−0.02	−0.13***	0.01	0.07***	0.01	−0.06**	0.01	−0.11***	1.00		
ELECTYR	**(25)**	0.05**	−0.02	0.02	−0.08***	−0.03	−0.01	−0.05**	0.01	−0.01	−0.05**	0.15***	1.00	
EPU	**(26)**	−0.03	−0.05**	−0.03	0.05**	−0.00	0.07***	0.03	0.01	0.05**	0.64***	−0.17***	−0.03	1.00

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note to Table 4: Table 4 presents Pearson correlations for the variables used in the regression analyses. The variables are identical and defined consistently, as specified in Table 3. All continuous variables are winsorized at the 1st and 99th percentiles.

Table 5
Relationship between Climate Policy Uncertainty and Analyst Forecast Quality.

	Dependent Variables:			
	$DISPAF_{y+1}$	$DISPAF_{ltg}$	$ABSFE_{y+1}$	$ABSFE_{ltg}$
Explanatory Variables	(1)	(2)	(3)	(4)
CPU	0.0030***	0.1301**	0.0026**	0.2084***
	(6.82)	(2.17)	(2.38)	(3.09)
AF_{y+1}	−0.0795***		−0.1420***	
	(−5.14)		(−3.60)	
AF_{ltg}		0.0390		0.4760***
		(0.50)		(3.39)
$FLLW_{y+1}$	0.0019		0.0042*	
	(1.65)		(1.89)	
$FLLW_{ltg}$		0.1105		−0.0137
		(1.35)		(−0.10)
SUR	0.3167***	1.9968	0.7930***	19.3916**
	(6.33)	(0.61)	(3.27)	(2.30)
ROA	0.0029	−0.2296	−0.0001	−0.4343
	(0.18)	(−0.23)	(−0.00)	(−0.12)
OCF	0.0378***	−0.7205	0.0683	2.0375
	(2.62)	(−0.70)	(1.62)	(0.67)
ROAVOL	0.1257***	8.3586**	0.2585***	6.8258
	(3.33)	(2.27)	(2.75)	(0.99)
LOSS	−0.0017	−0.0141	0.0059	−0.0906
	(−0.56)	(−0.04)	(0.83)	(−0.15)
M&A	0.0006	−0.0503	0.0009	0.1279
	(0.92)	(−0.85)	(0.63)	(1.53)
LEV	−0.0065***	−0.3428*	−0.0156***	−0.3542
	(−2.77)	(−1.83)	(−3.51)	(−1.29)
BTM	0.0002*	0.0111	0.0007**	0.0173*
	(1.74)	(1.51)	(2.15)	(1.77)
INTAN	0.0213***	1.0285***	0.0310***	2.2945***
	(8.10)	(3.41)	(6.00)	(4.69)
SIZE	−0.0011**	−0.0806**	−0.0016**	−0.1592***
	(−2.51)	(−2.24)	(−2.22)	(−3.24)
BIG4	0.0003	0.3026	0.0022	0.0739
	(0.21)	(1.26)	(0.40)	(0.13)
HHI	0.0061	−0.7296	−0.0069	−0.0941
	(1.14)	(−1.12)	(−0.62)	(−0.11)
EMV	0.0046***	0.2441**	0.0010	0.3513***
	(5.54)	(2.36)	(0.60)	(3.26)
ROLLCALLS	0.0006*	−0.0550	0.0007	−0.0487
	(1.96)	(−1.43)	(1.21)	(−0.96)
ELECTYR	0.0001	−0.0594	0.0021*	0.1189
	(0.13)	(−1.31)	(1.91)	(1.23)
EPU	0.0042***	0.1560	0.0074***	−0.0291
	(3.98)	(1.63)	(3.35)	(−0.20)
Intercept	*Included*	*Included*	*Included*	*Included*
Industry Fixed Effect	*Included*	*Included*	*Included*	*Included*
N	2025	2025	2025	2025
R^2	0.5837	0.1965	0.5063	0.3964
R^2_{adj}	0.5714	0.1728	0.4917	0.3786

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note to Table 5**:** This table reports the results for variants of the following regression models:
$DISPAF_\tau = a_0 + a_1 CPU + a_2 AF_\tau + a_3 FLLW_\tau + a_4 SUR + a_5 ROA + a_6 OCF + a_7 ROAVOL + a_8 LOSS + a_9 M\&A + a_{10} LEV + a_{11} BTM + a_{12} INTAN + a_{13} SIZE + a_{14} BIG4 + a_{15} HHI + a_{16} EMV + a_{17} ROLLCALLS + a_{18} ELECTYR + a_{19} EPU + Industry\ Fixed\ Effects + \varepsilon$ [2a]
$ABSFE_\tau = b_0 + b_1 CPU + b_2 AF_\tau + b_3 FLLW_\tau + b_4 SUR + b_5 ROA + b_6 OCF + b_7 ROAVOL + b_8 LOSS + b_9 M\&A + b_{10} LEV + b_{11} BTM + b_{12} INTAN + b_{13} SIZE + b_{14} BIG4 + b_{15} HHI + b_{16} EMV + b_{17} ROLLCALLS + b_{20} ELECTYR + b_{19} EPU + Industry\ Fixed\ Effects + \varepsilon$ [2b]
We use ordinary least squares regression to estimate the above models and report the results in columns (1) and (2). Standard errors are adjusted for firm clustering effects. Variables are defined as follows: ***CPU*** = Natural logarithm of the average Climate Policy Uncertainty index value during the 3-month period following the annual earnings announcement. $\boldsymbol{DISPAF_\tau}$ = Analyst forecast dispersion for one-year ahead earnings ($\tau = y+1$) or long-term earnings growth rate ($\tau = ltg$). $\boldsymbol{ABSFE_\tau}$ = Absolute error in analyst forecasts for one-year ahead earnings ($\tau = y+1$) or long-term earnings growth rate ($\tau = ltg$). $\boldsymbol{AF_\tau}$ = Analyst forecast for one-year-ahead earnings ($\tau = y+1$) or long-term earnings growth rate ($\tau = ltg$). $\boldsymbol{FLLW_\tau}$ = Number of analysts covering the firms' one-year-ahead earnings ($\tau = y+1$), or long-term earnings growth rate ($\tau = ltg$). ***SUR*** = Earnings surprise. ***ROA*** = Return on assets. ***OCF*** = Cash flows from operating activities. ***ROAVOL*** = Volatility of quarterly return on assets over the previous 8 quarters. ***LOSS*** = Operating loss indicator. ***M&A*** = Merger and acquisition indicator. ***LEV*** = Financial leverage. ***BTM*** = Book-to-market ratio. ***INTAN*** = Intangible assets. ***SIZE*** = Firm size. ***BIG4*** = Audited by big-four CPA firms. ***HHI*** = Herfindahl-Hirschman Index. ***EMV*** = Natural logarithm of the average Equity Market Volatility index value during the 3-month period following the annual earnings announcement. ***ROLLCALLS*** = Natural logarithm of the number of roll-call voting in Congress during the 3-month period following the annual earnings announcement. ***ELECTYR*** = Indicator of whether annual earnings announcement occurs during presidential election year. ***EPU*** = Natural logarithm of the average Economic Policy Uncertainty index value during the 3-month period following the annual earnings announcement. See the appendix for detailed variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles.

longer-horizon forecasts (columns (2) and (4)).

4.3. Results of cross-sectional analyses

4.3.1. Political gridlock

Table 6 presents the results for H2a, which examines the interactive effect of climate policy uncertainty (CPU^d) and political gridlock (*GRIDLOCK*) on analyst forecast quality. Significance levels are based on standard errors adjusted for firm clustering effects, and control variables are included but not reported for brevity.

In Panel A, columns (1) and (2) present regression results from eq. [4a], using forecast dispersion for short- and long-horizon earnings as the dependent variables. Columns (3) and (4) report results from eq. [4b], with absolute forecast error as the dependent variable. Consistent with previous findings, the coefficient on CPU^d is positive and highly significant ($p < 0.01$) across all columns. Although the coefficients on *GRIDLOCK* are not significantly different from zero, the interaction term between CPU^d and *GRIDLOCK* is consistently negative and highly significant ($p < 0.01$), except in column (2). These findings support H2a that political gridlock mitigates the adverse effects of climate policy uncertainty on analyst forecast quality. The mitigating effect arises when legislative processes slow down or stall due to conflicting interests, party polarization, or institutional barriers, reducing uncertainty about future climate-related legislation and easing analysts' forecasting challenges.

As discussed in Section 3.4, political gridlock, influenced by ideological polarization, occurs when the average political ideologies of congressional members from opposing parties diverge significantly. To test whether extreme ideologies from either side could bias our *GRIDLOCK* variable and affect the results, we reanalyzed the data using alternative definitions of *GRIDLOCK* based on polarization between party leaders ($GRIDLOCK_{party\ leader}$) and between party whips ($GRIDLOCK_{whip}$). Given their roles in advancing the party's legislative agenda, these positions may better capture the party's stance on various issues.

Panels B and C of Table 6 display the results using these alternative measurements. Panel B shows that the coefficients on $GRIDLOCK_{party\ leader}$ are consistently negative and significant ($p < 0.01$). Similarly, Panel C indicates that the coefficients on $GRIDLOCK_{whip}$ are consistently negative and significant ($p < 0.05$), except in column (2). In both panels, the coefficients for the interaction terms between CPU^d and $GRIDLOCK_{party\ leader}$ or $GRIDLOCK_{whip}$ are consistently negative and generally significant. Thus, our results on the role of political gridlock remain robust regardless of the measurement of the variable.

4.3.2. Financial reporting disclosure quality

Table 7 presents the results for H2b, which examines the interactive effect of climate policy uncertainty (CPU^d) and financial reporting

Table 6
Effect of Political Gridlock on Climate Policy Uncertainty and Financial Analysts Forecast Quality.

Panel A. Ideological Polarization of *all* Congressional Members

	Dependent Variables:			
	$DISPAF_{y+1}$	$DISPAF_{ltg}$	$ABSFE_{y+1}$	$ABSFE_{ltg}$
Explanatory Variables	(1)	(2)	(3)	(4)
CPU^d	0.0159***	0.5060***	0.0216***	0.9128***
	(7.36)	(2.75)	(5.07)	(3.18)
GRIDLOCK	0.0001	0.0039	0.0001	0.0039
	(0.92)	(0.63)	(0.96)	(0.36)
$CPU^d \times GRIDLOCK$	−0.0011***	−0.0185	−0.0018***	−0.0585**
	(−6.81)	(−1.52)	(−5.67)	(−2.32)
Intercept & Controls	*Included*	*Included*	*Included*	*Included*
Industry Fixed Effect	*Included*	*Included*	*Included*	*Included*
N	2025	2025	2025	2025
R^2	0.4814	0.1587	0.4610	0.3282
R^2_{adj}	0.4655	0.1329	0.4445	0.3076

Panel B. Ideological Polarization of Congressional Leaders

	Dependent Variables:			
	$DISPAF_{y+1}$	$DISPAF_{ltg}$	$ABSFE_{y+1}$	$ABSFE_{ltg}$
Explanatory Variables	(1)	(2)	(3)	(4)
CPU^d	0.0116***	0.1026	0.0157***	0.5116*
	(5.38)	(0.54)	(3.54)	(1.84)
$GRIDLOCK_{Party\ Leader}$	−0.0002***	−0.0063***	−0.0002***	−0.0137***
	(−6.04)	(−2.70)	(−4.07)	(−3.89)
$CPU^d \times GRIDLOCK_{Party\ Leader}$	−0.0004***	0.0061	−0.0007***	−0.0163
	(−5.11)	(0.78)	(−4.22)	(−1.45)
Intercept & Controls	*Included*	*Included*	*Included*	*Included*
Industry Fixed Effect	*Included*	*Included*	*Included*	*Included*
N	2025	2025	2025	2025
R^2	0.4914	0.1604	0.4658	0.3319
R^2_{adj}	0.4758	0.1347	0.4494	0.3114

Panel C. Ideological Polarization of Party Whips in Congress

	Dependent Variables:			
	$DISPAF_{y+1}$	$DISPAF_{ltg}$	$ABSFE_{y+1}$	$ABSFE_{ltg}$
Explanatory Variables	(1)	(2)	(3)	(4)
CPU^d	0.0401***	0.6725	0.0588***	2.0602**
	(6.93)	(1.42)	(5.42)	(2.46)
$GRIDLOCK_{Party\ Whip}$	−0.0005***	−0.0214	−0.0008**	−0.0482**
	(−2.79)	(−1.14)	(−2.41)	(−2.30)
$CPU^d \times GRIDLOCK_{Party\ Whip}$	−0.0033***	−0.0339	−0.0052***	−0.1650**
	(−6.67)	(−0.81)	(−5.58)	(−2.14)
Intercept & Controls	*Included*	*Included*	*Included*	*Included*
Industry Fixed Effect	*Included*	*Included*	*Included*	*Included*
N	2025	2025	2025	2025
R^2	0.4831	0.1589	0.4621	0.3289
R^2_{adj}	0.4672	0.1332	0.4456	0.3084

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note to Table 6: This table reports the results for variants of the following regression models:

$DISPAF_\tau = a_0 + a_1 CPU^d + a_2 GRIDLOCK + a_3 CPU^d \times POLAR_k + Control\ Variables + \varepsilon$ [4a]

$ABSFE_\tau = b_0 + b_1 CPU^d + b_2 GRIDLOCK + b_3 CPU^d \times POLAR_k + Control\ Variables + \varepsilon$ [4b]

We use ordinary least squares regression to estimate the above models and report the results in columns (1) and (2). Standard errors are adjusted for firm clustering effects. Control variables are included but not reported for brevity. Variables are defined as follows: $\boldsymbol{DISPAF_\tau}$ = Analyst forecast dispersion for one-year ahead earnings ($\tau = y + 1$) or long-term earnings growth rate ($\tau = ltg$). $\boldsymbol{ABSFE_\tau}$ = Absolute error in analyst forecasts for one-year ahead earnings ($\tau = y + 1$) or long-term earnings growth rate ($\tau = ltg$). $\boldsymbol{CPU^d}$ = Indicator of high Climate Policy Uncertainty. ***GRIDLOCK*** = Political gridlock, defined as a combination of political party polarization and divided control between the executive and legislative branches. $\boldsymbol{GRIDLOCK_{party\ leader}}$ = Political gridlock, defined as a combination of political polarization of congressional leaders and divided control between the executive and legislative branches.

$\boldsymbol{GRIDLOCK_{party_{whip}}}$ = Political gridlock, defined as a combination of political polarization of party whips congress and divided control between the executive and legislative branches. The control variables are the same as those specified in eqs. [2a] and [2b]. See the appendix for detailed variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles.

disclosure quality ($FRDQ_{\theta}$) on analyst forecast quality.

In Panel A, financial reporting disclosure quality is proxied by an indicator variable for low absolute abnormal accruals ($FRDQ_{abacc}$). The coefficients on CPU^d are consistently negative and generally statistically significant. The coefficients on $FRDQ_{abacc}$ are also consistently negative and significant, indicating that better financial reporting (i.e., lower abnormal accruals) is associated with improved forecast quality, except in column (4) where significance is not observed. The interaction term between CPU^d and $FRDQ_{abacc}$ is consistently negative and highly significant ($p < 0.01$).

In Panel B, we use a principal component score ($FRDQ_{score}$), which consolidates factors reflecting high disclosure quality. The coefficients on CPU^d remain consistently negative and statistically significant. While the coefficients on $FRDQ_{score}$ are significantly different from zero, we observe that the interaction term between CPU^d and $FRDQ_{score}$ is consistently negative and significant ($p < 0.10$).

In summary, these results support the hypothesis that higher financial disclosure quality mitigates the negative impact of climate policy uncertainty on analyst forecast quality. This suggests that firms with better disclosure practices provide more reliable information, enabling analysts to make more accurate forecasts even amidst uncertain climate policies.

4.3.3. Financial analyst forecast expertise

Table 8 explores H2c on the effect of analyst expertise on forecast quality, focusing on analysts' average industry experience ($EXPRT_{ind\ exp}$) and their affiliation with large brokerage houses ($EXPRT_{largebroker}$). The results are presented in Panels A and B, respectively.

In Panel A, the coefficients on CPU^d are consistently negative and statistically significant across all columns, highlighting the adverse impact of climate policy uncertainty on forecast quality. The coefficients on $EXPRT_{ind\ exp}$ are negative and significant ($p < 0.05$) in columns (2) and (4), indicating that greater industry experience improves forecast quality, especially for long-horizon forecasts. As expected, the interaction between CPU^d and $EXPRT_{ind\ exp}$ is also consistently negative, with significant results in columns (2) and (4).

Panel B examines $EXPRT_{largebroker}$, which indicates whether the majority of the analysts are affiliated with large brokerage houses. The coefficients on $EXPRT_{largebroker}$ are statistically insignificant across all columns, suggesting that affiliation with large brokerage houses does not significantly help analysts differentiate themselves when macroeconomic information is less uncertainty. Similar to Panel A, the coefficients on CPU^d remain consistently negative and significant ($p < 0.05$), and the interaction between CPU^d and $EXPRT_{largebroker}$ is consistently negative and significant ($p < 0.05$).

Overall, the findings suggest that analyst expertise, captured by analysts experience and affiliation with larger brokerage, has a varied impact on forecast quality. Specifically, the results on the interactive effect of climate policy uncertainty and analyst expertise support the hypothesis that greater expertise, particularly through affiliation with larger brokerage, helps mitigate the negative impact of climate policy uncertainty on forecast quality.

Table 7
Effect of Financial Reporting Disclosure Quality on Climate Policy Uncertainty and Financial Analysts Forecast Quality

Panel A. Disclosure Quality proxied by Absolute Abnormal Accruals

	Dependent Variables:			
	$DISPAF_{y+1}$	$DISPAF_{ltg}$	$ABSFE_{y+1}$	$ABSFE_{ltg}$
Explanatory Variables	(1)	(2)	(3)	(4)
$\boldsymbol{CPU^d}$	0.0043***	0.2935**	0.0032	0.3054**
	(4.88)	(2.36)	(1.58)	(2.41)
$\boldsymbol{FRDQ_{abacc}}$	−0.0013***	−0.0498**	−0.0019***	−0.0114
	(−5.51)	(−2.22)	(−3.45)	(−0.34)
$\boldsymbol{CPU^d \times FRDQ_{abacc}}$	−0.0039***	−0.2667***	−0.0052***	−0.2350***
	(−6.75)	(−2.71)	(−4.89)	(−2.64)
Intercept and Controls	*Included*	*Included*	*Included*	*Included*
Industry Fixed Effect	*Included*	*Included*	*Included*	*Included*
N	2025	2025	2025	2025
$\boldsymbol{R^2}$	0.5185	0.1855	0.4531	0.3399
$\boldsymbol{R^2_{adj}}$	0.5037	0.1604	0.4362	0.3196

Panel B. Disclosure Quality proxied by Composite Disclosure Score

	Dependent Variables:			
	$DISPAF_{y+1}$	$DISPAF_{ltg}$	$ABSFE_{y+1}$	$ABSFE_{ltg}$
Explanatory Variables	(1)	(2)	(3)	(4)
$\boldsymbol{CPU^d}$	0.0060***	0.4199***	0.0052**	0.4014***
	(6.18)	(2.66)	(2.56)	(2.78)
$\boldsymbol{FRDQ_{score}}$	0.0008	−0.0159	−0.0001	−0.0427
	(1.57)	(−0.38)	(−0.05)	(−0.60)
$\boldsymbol{CPU^d \times FRDQ_{score}}$	−0.0052**	−0.4463**	−0.0068**	−0.3531*
	(−2.55)	(−2.39)	(−2.39)	(−1.92)
Intercept and Controls	*Included*	*Included*	*Included*	*Included*
Industry Fixed Effect	*Included*	*Included*	*Included*	*Included*
N	2025	2025	2025	2025
$\boldsymbol{R^2}$	0.4746	0.1620	0.4557	0.3277
$\boldsymbol{R^2_{adj}}$	0.4585	0.1364	0.4390	0.3072

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note to Table 7: This table reports the results for variants of the following regression models:

$DISPAF_{\tau} = a_0 + a_1 CPU^d + a_2 FRDQ_{\theta} + a_3 CPU^d \times FRDQ_{\theta} + Control\ Variable + \varepsilon$ [5a]

$ABSFE_{\tau} = b_0 + b_1 CPU^d + b_2 FRDQ_{\theta} + b_3 CPU^d \times FRDQ_{\theta} + Control\ Variable + \varepsilon$ [5b]

We use ordinary least squares regression to estimate the above models and report the results in columns (1) and (2). Standard errors are adjusted for firm clustering effects. Control variables are included but not reported for brevity. Variables are defined as follows: $\boldsymbol{DISPAF_{\tau}}$ = Analyst forecast dispersion for one-year ahead earnings ($\tau = y+1$) or long-term earnings growth rate ($\tau = ltg$). $\boldsymbol{ABSFE_{\tau}}$ = Absolute error in analyst forecasts for one-year ahead earnings ($\tau = y+1$) or long-term earnings growth rate ($\tau = ltg$). $\boldsymbol{CPU^d}$ = Indicator of high Climate Policy Uncertainty. $\boldsymbol{FRDQ_{\theta}}$ = Financial reporting disclosure quality, measured by indicator of low absolute abnormal accruals ($\theta = abacc$) or disclosure quality score ($\theta = score$). The control variables are the same as those specified in eqs. [2a] and [2b]. See the appendix for detailed variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles.

5. Additional analyses

5.1. Climate policy uncertainty and climate risk disclosure

In this section, we extend our analysis to explore whether firms preempt the negative impact of climate policy uncertainty through improved disclosure. Prior research and business commentary suggest that conference calls are a common medium for earnings announcements. Beyond mandatory reporting, managers often voluntarily share additional information during these calls to help investors better understand firm-specific financial data (Baginski, Hassell, & Kimbrough, 2004; Billings, Jennings, & Lev, 2015), risk exposure (Deumes & Knechel, 2008; Flammer et al., 2021; Jorgensen & Kirschenheiter, 2003), industry conditions, as well as regulatory environment (Bonsall IV, Bozanic, & Fischer, 2013; Choi et al., 2024).

Building on this literature, we extend our research to explore two key questions in the context of climate policy uncertainty: (1) whether managers attempt to preempt the negative effects of climate policy uncertainty by discussing the firm's climate risk exposure and strategic responses to potential changes in climate policies during conference

Table 8
Effect of Financial Analyst Macroeconomic Expertise on Climate Policy Uncertainty and Financial Analysts Forecast Quality.

Panel A. Macroeconomic Expertise measured by Analysts' Industry Experience

	Dependent Variables:			
	$DISPAF_{y+1}$	$DISPAF_{ltg}$	$ABSFE_{y+1}$	$ABSFE_{ltg}$
Explanatory Variables	(1)	(2)	(3)	(4)
$\boldsymbol{CPU^d}$	0.0050***	0.3719**	0.0044**	0.3746***
	(5.58)	(2.57)	(2.19)	(2.60)
$\boldsymbol{EXPRT_{ind\ exp}}$	0.0001	−0.1257**	0.0007	−0.2060**
	(0.11)	(−2.30)	(0.44)	(−2.39)
$\boldsymbol{CPU^d \times EXPRT_{ind\ exp}}$	−0.0026	−0.3662**	−0.0055	−0.4719**
	(−1.16)	(−2.03)	(−1.37)	(−2.33)
Intercept and Controls	*Included*	*Included*	*Included*	*Included*
Industry Fixed Effect	*Included*	*Included*	*Included*	*Included*
$\boldsymbol{N}$	2025	2025	2025	2025
$\boldsymbol{R^2}$	0.4788	0.1582	0.4369	0.2921
$\boldsymbol{R^2_{adj}}$	0.4623	0.1314	0.4189	0.2695

Panel B. Macroeconomic Expertise measured by Analyst's Affiliation of Large Brokerage House

	Dependent Variables:			
	$DISPAF_{y+1}$	$DISPAF_{ltg}$	$ABSFE_{y+1}$	$ABSFE_{ltg}$
Explanatory Variables	(1)	(2)	(3)	(4)
$\boldsymbol{CPU^d}$	0.0052***	0.3436***	0.0042**	0.3683***
	(6.02)	(2.67)	(2.17)	(2.90)
$\boldsymbol{EXPRT_{large\ broker}}$	0.0015	−0.0410	0.0022	0.2998
	(0.71)	(−0.51)	(0.79)	(0.96)
$\boldsymbol{CPU^d \times EXPRT_{large\ broker}}$	−0.0075***	−0.5534**	−0.0099**	−0.9863***
	(−2.67)	(−2.38)	(−2.30)	(−2.76)
Intercept and Controls	*Included*	*Included*	*Included*	*Included*
Industry Fixed Effect	*Included*	*Included*	*Included*	*Included*
$\boldsymbol{N}$	2025	2025	2025	2025
$\boldsymbol{R^2}$	0.4733	0.1599	0.4548	0.3282
$\boldsymbol{R^2_{adj}}$	0.4572	0.1342	0.4381	0.3076

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note to Table 8: This table reports the results for variants of the following regression models:

$DISPAF_\tau = a_0 + a_1 CPU^d + a_2 EXPRT_\lambda + a_3 CPU^d \times EXPRT_\lambda + \textit{Control Variables} + \varepsilon$ [6a]

$ABSFE_\tau = b_0 + b_1 CPU^d + b_2 EXPRT_\lambda + b_3 CPU^d \times EXPRT_\lambda + \textit{Control Variables} + \varepsilon$ (6b)

We use ordinary least squares regression to estimate the above models and report the results in columns (1) and (2). Standard errors are adjusted for firm clustering effects. Control variables are included but not reported for brevity. Variables are defined as follows: $\boldsymbol{DISPAF_\tau}$ = Analyst forecast dispersion for one-year ahead earnings ($\tau = y+1$) or long-term earnings growth rate ($\tau = ltg$). $\boldsymbol{ABSFE_\tau}$ = Absolute error in analyst forecasts for one-year ahead earnings ($\tau = y+1$) or long-term earnings growth rate ($\tau = ltg$). $\boldsymbol{CPU^d}$ = Indicator of high Climate Policy Uncertainty. $\boldsymbol{EXPRT_\lambda}$ = Indicator of higher industry experience among following analysts (λ = *ind exp.*) or of greater representation of larger brokerage house among following analysts (λ = *large broker*). The control variables are the same as those specified in eqs. [2a] and [2b]. See the appendix for detailed variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles.

calls, and (2) whether increased climate-related discussion during these calls mitigates the negative impact of climate policy uncertainty on analyst forecast quality.

For the first analysis, we examine the likelihood ($Prob(DISC > 0)$) and extent (*DISC*) of climate-related disclosures during conference calls, regressing these against climate policy uncertainty while controlling for other firm-specific characteristics. Data on *DISC* is sourced from Sautner, Van Lent, Vilkov, and Zhang (2023), who developed a machine learning algorithm to analyze quarterly earnings call transcripts. The algorithm identifies climate-related and non-climate-related bigrams in both management presentations and Q&A sessions. Firm-specific climate risk exposure is calculated for each quarterly call transcript as the number of climate-related bigrams divided by the total number of bigrams, with annual exposure being the average of the quarterly measures.[16]

Table 9 presents the results. Columns (1) and (2) show that the coefficients on CPU^d are consistently positive and statistically significant, indicating that higher climate policy uncertainty increases the likelihood and extent of climate-related disclosures during conference calls.

In the second analysis, we regress measurements of analyst forecast quality—specifically forecast dispersion and absolute forecast error across different forecast horizons—on periods of high climate policy uncertainty (CPU^d), climate-related disclosures (*DISC*), and the interaction between these variables. Table 10 shows that while the coefficients on *DISC* are consistently insignificant, the interaction between CPU^d and *DISC* is consistently negative and significant.

Overall, the findings suggest that managers are instrumental in helping analysts navigate the challenges of climate policy uncertainty. By proactively addressing climate risks and strategic responses during conference calls, managers can significantly reduce the uncertainty analysts face, thereby enhancing forecast quality. This underscores the importance of transparent and comprehensive communication, especially in uncertain regulatory environments.

5.2. Robustness check

In Table 5, we demonstrated that analyst forecast quality is adversely affected by climate policy uncertainty, measured by a monthly index developed by Gavriilidis (2021). To assess the robustness of this finding, we perform two additional analyses: (1) to evaluate whether our findings are sensitive to alternative measurements of climate policy uncertainty, and (2) to examine whether our findings are biased due to potential endogeneity between climate policy uncertainty and general economic policy uncertainty.

In the first robustness check, we remeasure climate policy uncertainty using the U.S. climate policy risk monthly index developed by Faccini et al. (2023). Similar to Gavriilidis (2021), Faccini et al. construct their index through newspaper content analysis. However, unlike Gavriilidis, who uses multiple newspapers, Facccini et al. focus exclusively on Reuters articles from the LSEG (formerly Refinitiv News Archive), analyzing content that includes the keywords 'climate change' and 'global warming.' The authors also manually screen these articles to ensure the accuracy of their measurement. Reanalyzing eqs. [2a] and [2b] using Facccini et al.'s monthly index, we find that the un-tabulated results align with our previous findings, confirming that climate policy uncertainty negatively impacts analyst forecast quality.

For the second robustness check, we evaluate the potential endogeneity between climate policy uncertainty and general economic policy uncertainty using an instrumental variable approach. First, we regress the climate policy uncertainty index (*CPU*) on two indexes: the global warming monthly index and natural disasters monthly index developed by Faccini et al. (2023). Then, we re-estimate eqs. [2a] and [2b] by replacing *CPU* with the predicted values from the first-stage regression ($\widehat{CPU}$). The unreported results show that the coefficient on $\widehat{CPU}$ is

[16] Conference calls consist of two main sessions: the manager's presentation and a Q&A session with financial analysts and other stakeholders. While the presentation focuses on company performance and strategy, the Q&A session includes questions and comments from listeners. Our measurement of conference calls, however, cannot differentiate between the manager's presentation and the Q&A session, nor can it isolate disclosures made specifically by managers during the Q&A. This potential measurement error may affect our empirical results, so readers should interpret our findings with caution.

Table 9
Climate Policy Uncertainty and Climate Risk Discussion during the Quarterly Earnings Conference-Call.

	Dependent Variables	
	$Prob(DISC > 0)$	*DISC*
Explanatory Variables	(1)	(2)
CPU	0.2250**	0.0540***
	(2.08)	(3.41)
$FLLW_y$	0.1446	−0.0386*
	(1.23)	(−1.87)
SUR	1.4679	−0.6674
	(0.32)	(−1.51)
ROA	−0.9675	0.1277
	(−0.67)	(0.95)
ROAVOL	−2.8740	−0.9998
	(−0.53)	(−1.09)
LOSS	0.0591	0.0501
	(0.12)	(1.49)
M&A	−0.0541	−0.0186
	(−0.28)	(−0.86)
OCF	−3.5121**	−0.6519***
	(−2.35)	(−2.85)
LEV	−0.0223	−0.0006
	(−0.48)	(−0.06)
INTAN	−0.8464*	−0.3765***
	(−1.72)	(−3.73)
BTM	0.0034	−0.0003
	(0.31)	(−0.12)
SIZE	−0.0417	0.0049
	(−0.71)	(0.41)
BIG4	0.3106	0.0909*
	(0.95)	(1.95)
HHI	5.2658**	0.1610
	(2.21)	(1.64)
Intercept	*Included*	*Included*
Industry Fixed Effect	*Included*	*Included*
N	2025	2025
Pseudo R^2	0.0895	
R^2		0.5777
R^2_{adj}		0.5663

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note to Table 9**:** This table reports the results for variants of the following regression models:

$$\left\{\begin{array}{c} Prob(DISC > 0) \\ DISC \end{array}\right\} = c_0 + c_1CPU + c_2FLLW_y + c_3SUR + c_4ROA + c_5OCF + c_6ROAVOL + c_7LOSS + c_8M\&A + c_9LEV + c_{10}BTM + c_{11}INTAN + c_{12}SIZE + c_{13}BIG4 + c_{14}HHI + Industry\ Fixed\ Effects + \varepsilon [7]$$

We use ordinary least squares regression to estimate the above models and report the results in columns (1) and (2). Standard errors are adjusted for firm clustering effects. Variables are defined as follows: $Prob(DISC > 0)$ = Likelihood of whether conference-call conversation related to climate-change issues occurs. ***DISC*** = Portion of conference-call conversation related to climate-change issues. ***CPU*** = Natural logarithm of the average Climate Policy Uncertainty index value during the 3-month period following the annual earnings announcement. ***$FLLW_y$*** = Number of analysts covering the firms' current year earnings. ***SUR*** = Earnings surprise. ***ROA*** = Return on assets. ***OCF*** = Cash flows from operating activities. ***ROAVOL*** = Volatility of quarterly return on assets over the previous 8 quarters. ***LOSS*** = Operating loss indicator. ***M&A*** = Merger and acquisition indicator. ***LEV*** = Financial leverage. ***BTM*** = Book-to-market ratio. ***INTAN*** = Intangible assets. ***SIZE*** = Firm size. ***BIG4*** = Audited by big-four CPA firms. ***HHI*** = Herfindahl-Hirschman Index. See the appendix for detailed variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles.

consistently positive and generally significant. This confirms that our primary findings regarding the relationship between CPU and analyst forecast quality are robust and not driven by potential endogeneity between climate policy uncertainty and general economic policy uncertainty.

Table 10
Effect of Climate Risk Discussion on Climate Policy Uncertainty and Financial Analysts Forecast Quality.

	Dependent Variables:			
	$DISPAF_{y+1}$	$DISPAF_{ltg}$	$ABSFE_{y+1}$	$ABSFE_{ltg}$
Explanatory Variables	(1)	(2)	(3)	(4)
CPU^d	0.0067***	0.4613***	0.0048**	0.4484***
	(6.74)	(2.86)	(2.33)	(3.11)
DISC	−0.0002	0.0008	−0.0000	0.0059
	(−0.25)	(0.02)	(−0.05)	(0.11)
$CPU^d \times DISC$	−0.0044***	−0.2608**	−0.0043***	−0.2389**
	(−5.26)	(−2.44)	(−3.48)	(−2.46)
Intercept & Controls	*Included*	*Included*	*Included*	*Included*
Industry Fixed Effect	*Included*	*Included*	*Included*	*Included*
N	2025	2025	2025	2025
R^2	0.4670	0.1561	0.4537	0.3264
R^2_{adj}	0.4515	0.1316	0.4378	0.3069

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note to Table 10**:** This table reports the results for variants of the following regression models:

$$DISPAF_\tau = a_0 + a_1CPU^d + a_2DISC + a_3CPU^d \times DISC + Control\ Variables + \varepsilon \quad [8a]$$

$$ABSFE_\tau = b_0 + b_1CPU^d + b_2DISC + b_3CPU^d \times DISC + Control\ Variables + \varepsilon \quad (8b)$$

We use ordinary least squares regression to estimate the above models and report the results in columns (1) and (2). Standard errors are adjusted for firm clustering effects. Control variables are included but not reported for brevity. Variables are defined as follows: ***$DISPAF_\tau$*** = Analyst forecast dispersion for one-year ahead earnings ($\tau = y + 1$) or long-term earnings growth rate ($\tau = ltg$). ***$ABSFE_\tau$*** = Absolute error in analyst forecasts for current-year earnings ($\tau = y$), one-year ahead earnings ($\tau = y + 1$), or long-term earnings growth rate ($\tau = ltg$). ***CPU^d*** = Indicator of high Climate Policy Uncertainty. ***DISC*** = Portion of conference-call conversation related to climate-change issues. The control variables are the same as those specified in eqs. [2a] and [2b]. See the appendix for detailed variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles.

6. Concluding remark

This study offers significant insights into the impact of climate policy uncertainty (CPU) on the quality of financial analysts' forecasts, particularly for GHG-intensive firms. Using the CPU index developed by Gavriilidis (2021), the analysis confirms its correlation with climate-related legislative activities and distinguishes it from general economic uncertainty indices. The findings reveal that CPU increases forecast dispersion and reduces accuracy, especially for long-term earnings forecasts. This suggests that the unpredictable nature of climate policy changes poses challenges for financial analysts, especially when forecasting the performance of firms heavily reliant on GHG emissions.

Furthermore, the study highlights how political factors and firm-specific characteristics interact with CPU to influence forecast quality. Political gridlock, typically viewed as an obstacle to policy advancement, unexpectedly mitigates the negative effects of CPU by creating a more stable regulatory environment for market participants. Additionally, firms with higher-quality financial disclosures and those followed by more experienced analysts are better able to navigate the challenges posed by CPU, resulting in less deterioration in forecast quality. This underscores the importance of transparency and expertise in mitigating the adverse effects of climate policy uncertainty.

Our research is not without limitations. First, CPU index may be influenced by increased media and societal focus on climate-related issues, rather than solely reflecting the actual uncertainty of climate policies. This media attention could amplify the perceived uncertainty, even when there are no significant legislative developments. As a result, the index might capture heightened public discourse rather than purely policy-driven uncertainty. We suggest that future research explore this potential bias by investigating the interaction between media coverage and actual policy shifts, and how these factors influence the CPU measure. Another limitation arises from the sample selection, which focuses on GHG-intensive firms subject to the Greenhouse Gas Reporting Program (GHGRP). Although these firms are particularly vulnerable to climate policy uncertainty, the findings may not be generalized to firms that could also be affected by CPU. Specifically, firms that do not meet GHGRP reporting thresholds could face different levels of government oversight and enforcement of climate policies, leading to varying levels of CPU exposure. Consequently, the conclusions drawn from this study may not fully reflect the broader impact of climate policy uncertainty across all sectors. Future research could broaden the sample to include a more diverse range of firms, assessing whether the effects of CPU are consistent in less GHG-intensive industries.

Declaration of interest and generative AI in scientific writing

The author do not have any financial and personal relationships with other people or organizations that could inappropriately influence (bias) their work. Furthermore, the authors acknowledge that no generative AI are used during the preparation of this work.

Declaration of competing interest

None.

Appendix A. Variable definition

Climate Policy Uncertainty Variable:		
CPU	=	Natural logarithm of the average value of monthly climate policy uncertainty index (Gavriilidis, 2021) during the three-month period following the annual earnings announcement.
$\boldsymbol{CPU^d}$	=	Indicator variable that equals 1 if the value of ***CPU*** is in the highest quintile of the sample distribution.
Financial Analyst Related Variables:		
$\boldsymbol{AF_\tau}$	=	Average value of I/B/E/S analysts forecast for one-year ahead earnings ($\tau = y+1$) or for long-term earnings growth rate ($\tau = ltg$), scaled by the stock price at the earnings announcement date. Analyst forecasts are those issued during the three-month period following the annual earnings announcement.
$\boldsymbol{ABSFE_\tau}$	=	Average of absolute I/B/E/S analyst forecast error for one-year ahead earnings ($\tau = y+1$) and long-term earnings growth rate ($\tau = ltg$), issued during the three-month period following the announcement, scaled by the stock price at the earnings announcement date. Analyst forecasts are those issued during the three-month period following the annual earnings announcement.
$\boldsymbol{DISPAF_\tau}$	=	Standard deviation of I/B/E/S analyst forecast for one-year ahead earnings ($\tau = y+1$) or for long-term earnings growth rate ($\tau = ltg$), scaled by the stock price at the earnings announcement date. Analyst forecasts are those issued during the three-month period following the annual earnings announcement.
$\boldsymbol{EXPRT_\lambda}$	=	Financial analyst industry expertise, measured in two ways: 1) **Industry experience (λ = *ind exp*):** an indicator variable that equals 1 if the average of following analysts' industry experience is in the top quintile of the sample distribution. Industry classification is based on three-digit NAICS code. 2) **Broker house size (λ = *large broker*):** an indicator variable that equals 1 if more than 50 % of the following analysts are affiliated with large brokerage houses. Large brokerage houses are defined as the top five brokerages employing the most analysts during the six-month period leading up to the current annual earnings announcement.
$\boldsymbol{FLLW_\tau}$	=	Natural logarithm of the number of I/B/E/S analysts covering current year earnings ($\tau = y$) during the 30-day period before the annual earnings announcement, or covering one-year ahead earnings ($\tau = y+1$) and long-term earnings growth rate ($\tau = ltg$) during the three-month period following the announcement.
SUR	=	Average of absolute error in I/B/E/S analyst forecasts of current year earnings, scaled by the stock price at the earnings announcement date. Analyst forecasts are those issued during the 30-day period before the annual earnings announcement.
Firm-Specific control variables:		
BIG4	=	Indicator variable that equals 1 if the firm's financial report is audited by either Ernst & Young, Deloitte & Touche, KPMG, or PricewaterhouseCoopers CPA firms (*COMPUSTAT* annual data item: *AU*).
BTM	=	Book-to-market ratio (*COMPUSTAT* annual data item: $CEQ/[PRCC\_F \times CSHO]$).
DISC	=	Proportion of the conference-call conversation related climate-change issues (Source: Sautner et al., 2023), multiplied by 100.
$\boldsymbol{FRDQ_\theta}$	=	Financial reporting disclosure quality, measured in two ways: 1) **Low absolute abnormal accruals (θ = *abacc*):** an indicator variable that equals 1 if the value of absolute abnormal accruals is in the highest quintile of the sample distribution. Abnormal accrual is estimated based on Dechow et al. (2003). 2) **Disclosure quality score (θ = *score*):** first principal component score based on the number of analysts following, analyst forecast accuracy, bid-ask spread, and trading volume (Baik et al., 2018).
INTAN	=	Intangible assets scaled by total assets (*COMPUSTAT* annual data item: $INTAN/AT$). Set to 0 if missing.
LEV	=	Total liability divided by book value of common shareholders' equity (*COMPUSTAT* annual data item: LT/CEQ).
LOSS	=	Indicator variable that equals 1 if the firm reports a loss (*COMPUSTAT* annual data item: *EBITDA*) in current fiscal year.
M&A	=	Indicator variable that equals 1 if the amount of acquisition expense (*COMPUSTAT* annual data item: *ACQ*) is greater or equal to 10 % of net sales during the current year (*COMPUSTAT* annual data item: *SALE*).
OCF	=	Operating activities net cash flow scaled by total assets (*COMPUSTAT* annual data item: $OANCF/AT$).
ROA	=	Earnings before interest, taxes, and depreciation, scaled by total assets (*COMPUSTAT* annual data item: $EBITDA/AT$).
ROAVOL	=	Standard deviation of quarterly *ROA* over the eight quarters preceding the current year's annual earnings announcement. Firm-year observations with less than three quarters of earnings information are excluded from the sample.
SIZE	=	Natural logarithm of market value of common equity (*COMPUSTAT* annual data item: $PRCC\_F \times CSHO$).
Other Policy and Macroeconomic related variables:		
$\boldsymbol{BILL_m^{Climate}}$	=	Percentage of bills introduced to the House of Representatives each month that pertain to climate policies. The status of these congressional bills is collected from the U.S. Government Publishing Office (data source: www.govinfo.gov). A bill is classified as climate-related if its title contains keywords from Gavriilidis's (2021) keyword library for climate policies.
$\boldsymbol{BILL_m^{\phi}}$	=	Percentage of bills introduced to the House of Representatives each month are categorized into fiscal policy and government spending ($\boldsymbol{\phi}$ = Fiscal), healthcare ($\boldsymbol{\phi}$ = Health), monetary policy ($\boldsymbol{\phi}$ = Monetary), national security ($\boldsymbol{\phi}$ = Security), and international trade ($\boldsymbol{\phi}$ = Trade). Information on the status of these

(*continued on next page*)

(*continued*)

		congressional bills is collected from the U.S. Government Publishing Office (www.govinfo.gov). A bill is categorized into a specific policy domain, such as international trade, if its title contains keywords from Baker et al. (2016) for various policy domains (www.policyuncertainty.com/categorical_terms.html).
ELECTYR	=	Indicator variable that equals 1 if the annual earnings announcement occurs between January 1 to November 5 of a presidential election year.
EMV	=	Natural logarithm of the average value of monthly US Equity Market Volatility Index during the three-month period following the annual earnings announcement (data source: www.policyuncertainty.com/).
EPU	=	Natural logarithm of the average value of monthly economic policy uncertainty index (Baker et al., 2016) during the three-month period following the annual earnings announcement.
$\boldsymbol{EPU^d}$	=	Indicator variable that equals 1 if the value of ***EPU*** is in the highest quintile of the sample distribution.
$\boldsymbol{HEAR_m^{Climate}}$	=	Percentage of public hearings each month that pertain to climate policies. The status of these congressional bills is collected from the U.S. Government Publishing Office (data source: www.govinfo.gov). A bill is classified as climate-related if its title contains keywords from Gavriilidis's (2021) keyword library for climate policies.
$\boldsymbol{HEAR_m^{\phi}}$	=	Percentage of public hearings held by congressional committees each month are categorized into fiscal policy and government spending (ϕ = Fiscal), healthcare (ϕ = Health), monetary policy (ϕ = Monetary), national security (ϕ = Security), and international trade (ϕ = Trade). Information on the status of these congressional bills is collected from the U.S. Government Publishing Office (www.govinfo.gov). A bill is categorized into a specific policy domain, such as international trade, if its title contains keywords from Baker et al. (2016) for various policy domains.
HHI	=	Herfindahl–Hirschman index, calculated as the sum of squared market shares based on sales revenue (*COMPUSTAT* annual data item: *SALE*) of the top five firms in the same market, defined by the three-digit NAICS code.
GRIDLOCK	=	Political gridlock, calculated as $\sum_c DIV_c \times POLAR_c$. DIV_c is an indicator variable that equals to 1 if during the three-month period following the current annual earnings announcement, the majority political party in the House (c = *House*) and the Senate (c = *Senate*), respectively, is different from the party the president is affiliated with. $POLAR_c$ is the difference in the average political ideology spectrum between the Democratics and the Republicans in the House (c = *House*) and the Senate (c = *Senate*), respectively. Political ideology spectrum of each Congress member is based on Poole and Rosenthal (2000) (data source: www.voteview.com).
$\boldsymbol{GRIDLOCK_\nu}$		Political gridlock, defined as *GRIDLOCK* expect for political polarization calculation is based on congressional party leaders (ν = *party leader*) or party whips in congress (ν = *party whip*).
ROLLCALLS	=	Natural logarithm of the number of roll-call voting in Congress during the three-month period following the annual earnings announcement (data source: www.voteview.com).

Data availability

Data will be made available on request.

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