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Measuring Climate Policy Uncertainty with LLMs: New Insights into Corporate Bond Credit Spreads[*]

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Abstract

This study examines the impact of climate policy uncertainty (CPU) on credit spreads using data from corporate bonds listed on the Chinese exchange market between 2008 and 2022. We innovatively apply large language models (LLMs) to construct a firm-level CPU index based on disclosure texts and validate its effectiveness. We find that a CPU rise widens a firm's credit spreads by exacerbating financial distress. Although disclosing environmental, social, and governance (ESG) information moderate CPU's effect on credit spreads, controversies in ESG ratings amplify it. Finally, heterogeneity analyses reveal that CPU's effect on widening bond spreads is more pronounced for traditional bonds, short- to medium-term bonds, non-state-owned enterprises, and issuing firms with dispersed supply chains.

Key Words: Climate policy uncertainty; Credit spread; Corporate bonds; LLMs

JEL Classification: G12; G32; Q54; M14

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1 Introduction

The carbon transition and limiting human-induced climate change have become critical issues globally. Governments worldwide are urgently implementing emissions reduction policies, particularly in major carbon-emitting countries. Consequently, firms face risks not only from the physical impacts of climate change, such as those from extreme weather on production and operations but also from policy uncertainty related to climate. This has been termed climate policy uncertainty (CPU) (Ginglinger and Moreau, 2023). The primary source of CPU comes from frequent government policy changes and inconsistent long-term commitments to climate initiatives (Gavriilidis, 2021). This can result from political lobbying, changes in political leadership, and short-term economic priorities (Meng and Rode, 2019; Noailly et al., 2022). The most obvious example of an unpredictable policy is the repeated shifts in the US government's climate policy. In 2015, the Obama administration committed to reducing greenhouse gases. However, in 2017, the Trump administration withdrew from the Paris Agreement. Finally, upon assuming office, the Biden administration quickly rejoined it (Mildenberger, 2021).

Studies predominantly examine the impact of physical climate risks by assessing firms' exposure to these risks. Jones and Olken (2010) investigated how international trade responds to temperature changes. Meanwhile, Huang et al. (2022) studied the impact of natural disasters on firm disclosure policies. However, the CPU literature differs in several ways. First, it often focuses on mature capital markets (Bouri et al., 2022; Jia et al., 2024). Second, firm-level CPU measures are lacking, making assessing their direct impact on individual companies difficult. Instead, macro-level CPU is usually used, such as in Dai and Zhang (2023) and Treepongkaruna et al. (2023). Furthermore, in the Chinese context, studies on CPU and bonds are mainly concentrated on green bonds (Tian et al., 2022; Ren et al., 2023), despite the vast majority of bond issuances being of traditional bonds. China's bond market is rather important in this context. Ranked second globally behind only the US, it has attracted increasing attention from foreign investors, especially since the launch of the Bond Connect program in 2017 (Shen, 2017). Given China's high carbon emissions and the concurrent implementation of emission reduction policies, investigating the effects of CPU on bond issuance practices in the Chinese bond market is crucial.

Addressing this question using firm disclosures, we make two key contributions to the literature on CPU and corporate finance. First, we innovatively employ large language models (LLMs), *ChatGPT* in particular, to construct a firm-level CPU index for Chinese-listed companies. In China, firm disclosures about climate risks are not comprehensive due to the non-mandatory nature of such information. Studies on US firms have constructed firm-level CPU indices using texts from earnings conference calls (Hossain et al., 2023; Sautner et al., 2023a). However, similar texts are only partially available in China. To address this limitation, we collect and analyze textual data from firms' corporate social responsibility (CSR) reports, Management Discussion and Analysis (MD&A) sections, and earnings communication conferences (ECCs), to comprehensively assess the CPU risks faced by individual firms. A significant challenge arises because different reporters describe climate risks in diverse and non-standardized ways (Sautner et al., 2023a). To overcome this, we utilize LLMs, which can analyze textual content similarly to human cognition. Extant research has demonstrated that LLMs effectively process, interpret, and access complex texts. Indeed, they are being increasingly applied in forecasts and evaluations in economic and finance research (Korinek, 2023; Kim et al., 2023; Manning et al., 2024; Jha et al., 2024).

Second, we examine the impact of CPU on corporate bond credit spreads and find that an increase in a firm's CPU widens its credit spread. This adds to the evidence of CPU's impact on other aspects such as corporate investment (Huang and Sun, 2023) and default risks (Liu et al., 2023). Additionally, we identify the primary channel through which CPU impacts firms: increased financial distress. Therefore, this study bridges the gap between CPU and corporate financial outcomes, providing valuable insights for academics and practitioners. Some argue that improvements in firms' environmental, social, and governance (ESG) performance may mitigate the negative impact of uncertainties (Raimo et al., 2021; Apergis et al., 2022; Trahan and Jantz, 2023). Indeed, we find that six commonly used ESG ratings in the Chinese market can alleviate the negative impact of CPU on credit spreads. Intriguingly, ESG rating divergence amplifies the negative effect of CPU, highlighting the importance of consistent ESG evaluations. This enriches the literature on ESG divergence (Avramov et al., 2022; Luo et al., 2023; Wang et al., 2024a). Overall, the findings contribute to the growing literature on the intersection of climate risk, ESG performance, and corporate finance. Lastly, heterogeneity analyses reveal that CPU's effect of widening bond credit spreads is more pronounced in traditional (non-green) and short-to-median-term bonds, non-state-owned enterprises (non-SOE), and issuing firms with dispersed supply chains.

The remainder of this article is organized as follows. Section 2 summarizes the relevant literature and develops the hypotheses. The model, data, and variable definitions are elaborated in Section 3. Section 4 reports the empirical results with economic explanations and robustness tests. Extensive analyses are conducted in Section 5, and we conclude in Section 6.

2 Literature Review and Hypotheses Development

2.1 Climate policy uncertainty and measurement

CPU refers to the ambiguity and unpredictability associated with the formulation, implementation, and future direction of policies aimed at addressing climate change (Gavriilidis, 2021; Ren et al., 2023). The uncertainty from climate policies can stem from various factors, including political changes, differing international commitments, and evolving scientific insights into climate change (Mokni et al., 2024). Kriegler et al. (2015) highlighted that extant climate policy is characterized by the ambitious long-term goal of limiting global warming to 2°C or less, contrary to the modest actions in the short-term, alongside significant doubts concerning future climate policies and the potential for reaching a global climate agreement. This means that CPU is significant and will likely persist long. Besides, technological advances impact the economics and politics of climate policy, increasing uncertainty and making it hard for businesses to predict the regulatory environment. This complex environment heightens the uncertainty for companies, hindering strategic planning, investment, and reputation management (Borozan and Pirgaip, 2024).

Specifically, the vagueness of governmental regulations concerning carbon emissions, renewable energy investments, and environmental safeguarding measures can profoundly influence corporations' operational expenses, market demand, and strategic future planning. This effect has been substantiated by various studies using stock market data. Xu et al. (2023) examined the relationship between CPU and fluctuations within China and the US stock markets. The results revealed that elevated CPU levels adversely affect short-term stock returns but may yield positive outcomes over the longer term. This highlights the market's initial reaction to uncertainty, followed by its eventual adjustment to policy shifts. Similarly, Treepongkaruna et al. (2023) identified a marked negative correlation between a firm's CPU exposure and its stock returns in the subsequent month, showing that compared to those who are more exposed, stocks less exposed to CPU on average, realize significantly higher future annual returns by 5.5%6.3%.

In addition to the stock market's reaction, several studies have examined how CPU affects corporate decision-making processes, such as investment behaviors. Hoang (2022) focused on US firms from 2000 to 2019 and found that CPU adversely impacts R&D investments, indicating firms' tendency to delay decision-making in response to changes in environmental policies greater clarity emerges. Ayed et al. (2024) highlighted CPU's significant role in shaping firms' dividend distribution strategies. Specifically, during periods of increased uncertainty prompted by indistinct climate policies, firms are likely to elevate their dividend distributions as a strategy to alleviate potential agency costs associated with free cash flow.

CPU is predominantly measured on a national level. Gavriilidis (2021) and Noailly et al. (2022) constructed the CPU index for the US, and Lee and Cho (2023) and Ma et al. (2023) compiled it for China. These national-level CPU measurements have provided valuable insights into macroeconomic uncertainties and their impacts. Nevertheless, with recent advancements in machine learning and LLMs, researchers have begun constructing firm-level CPUs using corporate disclosure information. However, this approach is currently limited to publicly listed companies in the US, whereby earnings call transcripts are utilized as the primary text source (Sautner et al., 2023b; Kim et al., 2023; Hossain et al., 2023).

2.2 CPU and credit spreads

The credit spread, defined as the difference between a bond's yield and a risk-free bond's yield, is a critical indicator for assessing the credit risk associated with a bond (Ge and Liu, 2015; Wang et al., 2022). From a corporate perspective, higher CPU can result in stricter environmental regulations and higher compliance costs. Further, the difficulty in accurately forecasting expenses from policy uncertainty poses financial planning challenges (Chen et al., 2019; Xu, 2020). It further causes investors and lenders to adopt a more cautious approach, thereby elevating the financing costs and difficulties for these firms, and leading to wider bond spreads upon issuance. Moreover, should firms need to restructure their capital to accommodate investments in green technologies and projects, they encounter refinancing risks during the transition (Siedschlag and Yan, 2021). This risk is particularly acute for firms requiring substantial capital to meet new policy mandates. Such a scenario can temporarily widen the bond spreads until the market understands the firm's capacity for sustainable long-term development.

From an investor's standpoint, Bolton and Kacperczyk (2023) highlighted that as global awareness and concern for climate change deepen among the public, governments, and institutional investors, they are increasingly recognizing the urgency of addressing climate challenges. This is reflected in the rising premia related to emissions. In this context, the uncertainty brought about by fluctuating climate policies can amplify the overall investment risk (Spiecker and Weber, 2014). Then, responding to this uncertainty, investors demand higher risk premia to offset potential policy changes. This adjustment in investor behavior directly leads to wider bond spreads for companies perceived to be at risk, underscoring market apprehensions about their future cash flows and ability to manage debt. Conversely, for bonds issued by firms that demonstrate superior adaptability to climate policies, have commendable environmental governance, or are green, the increase in bond spread may be less pronounced or even diminish under certain conditions, despite heightened CPU (Nanayakkara and Colombage, 2019; Piñeiro-Chousa et al., 2021). Accordingly, we propose the following hypothesis:

Hypothesis 1: *An increase in CPU is associated with wider corporate credit spreads.*

2.3 CPU and financial distress

Corporate financial distress refers to a situation where a firm struggles to meet its debt obligations, leading to strained cash flow, declining credit ratings, and rising financing costs, among other unfavorable financial conditions (Meng et al., 2024). When CPU rises, companies must deal with unpredictable environmental regulations and standards, increasing capital costs and financing expenses. Consequently, firms reduce their reliance on external funding, which diminishes their cash flow (Xu, 2020), thereby increasing the likelihood of financial distress. Moreover, Gulen and Ion (2016) found that uncertainty about future policies inhibits corporate investments; moreover, it takes two to three years for investments to recover after experiencing the effects of policy uncertainty. Chen et al. (2019) also discovered that companies reduce their investments when faced with higher policy uncertainty. Delayed or reduced investments may cause firms to miss market opportunities. This can affect their cash flow and long-term profits, further increasing the risk of financial distress. The uncertainty in cash flow resulting from financial distress reduces the quality of information contained in stock prices, limiting the information available to investors (Drobetz et al., 2018). Consequently, financial distress leads investors and lenders to adopt a more cautious attitude, leading to wider bond spreads on issuance. Accordingly, we propose the following hypothesis:

Hypothesis 2: *CPU increases corporate financial distress, thereby widening corporate credit spreads.*

2.4 Effects from ESG disclosure

As the focus on ESG increases, ESG performance has become an important criterion influencing investors' investment decisions (Gillan et al., 2021; Zhou et al., 2024). Trahan and Jantz (2023) noted that the ESG framework is closely related to combating climate change. ESG ratings mitigate information asymmetry through information disclosure, enabling investors to assess a company's risks and potential returns more clearly(Cui et al., 2018). Consequently, investors are often willing to accept a lower risk premium for companies with high ESG performance, thereby increasing companies' financing opportunities. Research shows that companies with high ESG ratings enjoy lower financing costs, which helps them access external funding under more favorable conditions (Raimo et al., 2021; Apergis et al., 2022). Zhou et al. (2024) found that good ESG performance reduces corporate opacity and default risk, leading to extended debt maturities and mitigating debt maturity mismatches. Reber et al. (2022) found that ESG information can effectively reduce the financial risks that initial public offering issuers and investors face in aftermarket trading. Chen et al. (2023) noted a significant positive correlation between ESG performance and financial performance, highlighting that "the positive impact of ESG ratings on financial performance is more pronounced in the high-risk case than in the low-risk case." This suggests that in environments with high CPU, higher ESG ratings typically correlate with lower credit risk and stronger financial performance, thereby narrowing bond spreads.

However, significant divergences in ESG ratings complicate investors' information processing. Due to the lack of unified measurement and interpretation standards, different rating providers may evaluate the same company's ESG performance differently (Chatterji et al., 2016; Berg et al., 2022a; Li et al., 2022). This divergence increases the cost of information processing. Consequently, investors will exercise greater caution when relying on ESG ratings(Wang et al., 2024a). Elamer and Boulhaga (2024) found ESG rating divergence has a negative effect on company performance. Li et al. (2022), Berg et al. (2022b), and Avramov et al. (2022) examined the impact of rating uncertainty in the stock market, revealing that rating uncertainty dampens stock demand and affects stock returns. Zou et al. (2023) found that ESG rating divergence leads investors to demand a higher risk premium, resulting in wider bond spreads. Although better ESG performance may mitigate the negative effects of CPU on bond spreads, divergences in ESG ratings can exacerbate the widening of spreads. Based on the above analysis, we propose the following hypotheses:

Hypothesis 3a: *Improving a company's ESG performance may mitigate CPU's negative impact on bond credit spreads.*

Hypothesis 3b: *ESG rating divergence exacerbates CPU's negative impact on bond credit spreads.*

3 Data and Model Specification

3.1 Sample selection

Our sample covers corporate bonds traded on the exchange and issued by non-financial firms in China for the period from 2008 to 2022. We lag firm-level control variables by one period in the regression model, and thus, they cover the period from 2007 to 2021; meanwhile, the remaining variables cover the period from 2008 to 2022. We selected this starting period because very few bonds were issued before 2008 and most non-governmental bonds featured external backing, with their interest rates predetermined by state authorities (Livingston et al., 2018). Moreover, we focus on these particular bonds for the following reasons. Amstad and He (2020) provided a detailed introduction to China's two major bond markets—the Over-the-Counter interbank and centralized exchange markets—as well as the three main categories of bonds: government, financial, and non-financial corporate bonds. Given our focus on corporate behavior, government bonds are excluded from the analysis. Furthermore, financial bonds are excluded because they are primarily issued by large banks with implicit government backing. Moreover, the same set of banks are the primary investors and underwriters in the primary market. Hence, financial bonds are distinctively different from non-financial bonds (Ding et al., 2022). Besides, the credit spreads of corporate bonds traded in the interbank market significantly differ from the classical ones commonly studied in the literature. Rather, the bond market in the Chinese exchange market is more comparable to Western corporate bond markets, with stricter information disclosure and audit regulation, as well as a more diversified set of participants (Chen and Jiang, 2021).

Accordingly, to obtain the final sample, we further filter out the following bonds: (1) Exclude bonds issued by financial institutions, international organizations, and government entities; (2) Exclude bonds maturing within one year; (3) drop defaulted bonds and those whose issuers are classified as ST or *ST, or have been delisted; and (4) drop observations with missing variables. The final sample comprises 4,959 bond-year observations with 1,553 corporate bonds issued by 578 unique listed firms. Financial data are collected from the CSMAR database, and scripts used for constructing CPU indexes are scoured from CNRDS, China Stock Market & Accounting Research (CSMAR), and CNINFO.

3.2 Basic model

We test our first hypotheses using Equation (1).

$$Spread_{ijt} = \alpha + \beta_1 CPUdivstd_{jt} + \beta_2 BondControls_{ijt} + \beta_3 IssuerControls_{j,t-1} + \lambda_j + \lambda_t + \varepsilon_{ijt} \quad (1)$$

where $Spread_{ijt}$ is the credit spread of the corporate bond i issued by firm j in year t. The key explanatory variable, $CPUdivstd$, represents the CPU shock. $BondControls$ and $IssuerControls$ are bonds and issuer control variables, respectively. To mitigate potential endogeneity, we lag $IssuerControls$ by one period. We include firm and year fixed effects, denoted by λ, and ε is the random error term.[1] We include firm and time-fixed effects to control for potential unobserved heterogeneity. Firm fixed effects are introduced to account for unobservable firm-level characteristics, such as industry-specific factors, that may influence the bond spread. Time-fixed effects are incorporated to eliminate the influence of temporal changes in macroeconomic conditions, such as fluctuations in the economic cycle or EPU changes, which can systematically affect bond spreads over different periods.

3.3 Variables

Credit spread: The credit spread of corporate bonds, $Spread$, is calculated as the difference in the yield-to-maturities (YTM) between corporate and treasury bonds of identical remaining duration, following Ge and Liu (2015) and Wang et al. (2022).

$$Spread_{it} = YTM_{it} - YTM_{gov,t} \quad (2)$$

where YTM_{it} is the YTM of the corporate bond i in year t using the yield on the last trading day. $YTM_{gov,t}$ is the YTM of the Chinese government bond with the same issuance and maturity time as the corporate bond in year t. The government bond data includes the YTMs for bonds with maturities of 5, 7, 10, 15, and 20 years. For any missing yields of government bonds in certain years, interpolation is employed to estimate the missing values as follows:

$$YTM_{gov,t} = YTM_{gov,t_1} + \frac{YTM_{gov,t_2} - YTM_{gov,t_1}}{t_2 - t_1} \times (t - t_1) \quad (3)$$

[1]Considering that our model controls for year fixed effects, market-level control variables such as gross domestic product (GDP), money supply, and economic policy uncertainty (EPU) are not included. In Table C.1 of Appendix C, we conduct an alternative regression by including market control variables while replacing the time-fixed effects; the results are similar to the baseline results.

where t_1 and t_2 are the years with known government bond yields, and t is the year for which the yield needs to be interpolated.

Climate policy uncertainty: Building on the work of Wang et al. (2023) and Wang (2023a), who used corporate disclosures to construct firm-level uncertainty indicators, and drawing on the approach of Kim et al. (2023) and Jha et al. (2024), who applied generative artificial intelligence (AI) techniques for text analysis, we propose a novel method to measure firm-specific CPU ($CPUdiv$).

Specifically, we apply generative AI techniques, following the approach of Kim et al. (2023) and Jha et al. (2024), to extract firm-specific CPU from companies' CSR reports, the MD&A section from annual reports, and ECCs. The annual CSR report is scraped from the CNINFO platform and converted into TXT format. MD&A sections are collected from the CNRDS database. Data on ECCs, which are held at irregular times, are sourced from the CSMAR database. In addition to MD&A, which is available for all firms annually, CSR reports and ECC scripts do not cover the entire sample of firms each year. To illustrate this coverage's extent, we aggregate the number of firms covered by CSR reports and ECC. Figure 1 presents the yearly count of firms with available CSR reports and those that held ECCs. Furthermore, MD&A ensures we have at least one document for each firm. Figure 2 illustrates the sample coverage in further detail. Notably, 18.5% of the observations are covered by all three documents. Approximately 68% of the sample is covered by at least two documents, MD&A and CSR, or MD&A and ECC.[2] [3] [4]

[Figure 1 about here.]

We divide the documents into chunks of 2,000 words and ensure that sentence boundaries are respected so that no single sentence is split across chunks. Dividing large documents into manageable pieces allows generative AI models to focus on smaller sections. This improves the accuracy and quality of content extraction, as the model tends to struggle with generating detailed summaries for longer documents, but performs comparably to humans when summarizing shorter texts (Choi et al., 2022). Therefore, following Kim et al. (2023), $CPUdiv$ is constructed as follows:

$$CPUdiv_{jt} = \frac{\sum_{l=1}^{K_{jt}} \text{len}\left(\mathbf{G}\left(c_{jt}^{l}\right)\right)}{\text{len}\left(c_{jt}\right)} \tag{4}$$

[2] The Shanghai Stock Exchange issued the "Guidelines on Social Responsibility for Listed Companies" in 2008. The Shenzhen Stock Exchange released similar guidelines in 2006. Both encourage the voluntary disclosure of ESG responsibilities, with mandatory environmental disclosures for high-pollution industries. Since 2008, the number of CSR reports and activities has surged (Marquis and Qian, 2014).

[3] Annual reports from listed companies are a reliable source of textual information. The China Securities Regulatory Commission mandates that companies disclose operational uncertainties in the MD&A section of annual reports. Wang et al. (2023) used this to construct firm-level EPU, while Wang (2023a) built firm-level political risk indicators.

[4] In China, ECCs provide real-time, interactive updates on company performance and outlook (Ding et al., 2024). Unlike earnings calls dominated by securities analysts' questions, earnings conferences allow any participant to ask questions, resulting in broader and potentially richer discussions. Additionally, questions at earnings conferences are posed live, limiting management's control over the information disclosed (Zhao et al., 2019).

where c_{jt} is transcript (i.e., CSR, MD&A and ECC) for firm j at time t, which is divided into K_{jt} chunks. $\mathbf{G}(\cdot)$ is the method (i.e., *gpt-4o-mini*) applied to the l-th chunk of the document for firm j at time t. $\text{len}(\mathbf{G}(\cdot))$ is the length of relevant text extracted from the l-th chunk and $\text{len}(c_{jt})$ is total length of the full transcript. By normalizing the length of the extracted relevant text relative to the total document length, $CPUdiv$ provides a consistent way to compare across firms and time periods.[5] Lastly, to remove the effects of scaling in our analysis, we standardize $CPUdiv$, denoted as $CPUdivstd$. Then, it can be written as:

$$CPUdivstd_{jt} = \frac{CPUdiv_{jt} - \mu(CPUdiv_{jt})}{\sigma(CPUdiv_{jt})} \tag{5}$$

where $\mu(CPUdiv_{jt})$ and $\sigma(CPUdiv_{jt})$ are the mean and standard deviations of $CPUdiv$, respectively.[6]

Control variables: Referring to Wang et al. (2022), Sun et al. (2023), and Ginglinger and Moreau (2023), we select control variables from the bond and issuer perspectives. Bond-related control variables include: BI, MAT, RDM, and PUT. Issuer-related control variables include: *Size*, *Age*, *ROA*, $FIXED$, *CR*, *Lev*, *Liquid*, $Top1$, and $INST$. The definitions are provided in Table 1.

[Table 1 about here.]

3.4 Descriptive statistical analysis

Table 2 presents the descriptive statistics for the dependent variable (*Spread*), key independent variable ($CPUdivstd$), and control variables. All variables are winsorized at the 1% and 99% levels to mitigate the effect of outliers. Our sample comprises 4,959 observations. The mean of $CPUdivstd$ is -0.009, with a maximum of 3.618 and a minimum of -1.042, indicating significant variation in the CPU faced by different firms. The mean of *Spread* is 2.084, with a minimum of 0.152 and a maximum reaching up to 6.641. All these values exceed the yield on government bonds, reflecting investors' demand for a higher yield to compensate for the additional risk they bear by investing in corporate bonds. Figure 3 plots the binned scatters of *Spread* against $CPUdivstd$, where each dot corresponds to a five percentile of the $CPUdivstd$ distribution and mean of *Spread* within each bin. To ensure that temporal changes or firm-specific characteristics do not confound the observed relationship, we control for both time and firm fixed effects. After adding the corresponding fitted, we notice a positive relationship between bond credit spread and CPU.

[5] We use OpenAI's *gpt-4o-mini*. The temperature parameter of the text generator is set to zero, and no strict limitation is imposed on the maximum output length. The *gpt-4o-mini* model can handle up to 128,000 tokens in a single instance. Hence, we do not need to worry about truncation. The prompts we input and sample snippets are provided in Appendix A.

[6] In the Appendix B, we present the probability distribution curve of $CPUdivstd$ (Figure B.1), calculate its Pearson correlation coefficients with other macro-level CPU indices (Table B.1), provide a time trend chart (Figure B.2) and a fitted plot (Figure B.3), and compare it with industry-level CO_2 emissions (Figure B.4) to validate the reliability of $CPUdivstd$.

[Table 2 about here.]

[Figure 2 about here.]

4 Empirical Analysis

4.1 Benchmark results

Table 3 presents the regression analysis results based on Equation (1), with the dependent ($Spread$) and key explanatory variables ($CPUdivstd$). Using the stepwise regression method, we progressively incorporate more control variables into the models from columns (1) to (3). Column (1) includes only the key explanatory variable $CPUdivstd$. In column (2), bond-level control variables are added, helping capture the impact of bond-specific characteristics on the spread. Column (3) further introduces firm-level control variables to account for the potential influence of a firm's financial condition, operational performance, and ownership structure on the bond spread. As more control variables are introduced, the adjusted R^2 of the model consistently increases, indicating an improvement in the model's explanatory power.

In Table 3, the coefficients of $CPUdivstd$ are positive across all regression specifications and statistically significant at the 5% level. This indicates a significant positive relationship between CPU and corporate bond credit spreads, as posited in **Hypothesis 1**. Thus, investors demand higher bond yields when assessing companies exposed to greater CPU. This demand reflects market expectations of uncertainty regarding these companies' future profitability and operating costs. CPU can increase future operating costs or reduce profitability, thereby weakening the company's debt repayment capacity. Hence, investors require higher yields to compensate for the increased credit risk.

According to column (3), after controlling for bond-specific and firm-level characteristics and a vector of control variables, the estimated coefficient for $CPUdivstd$ is significantly positive at the 5% level, with a value of 0.145. Thus, an increase in $CPUdivstd$ by one standard deviation significantly increases the credit spread by 0.139 ($0.962 \times 0.145 = 0.139$) units, which is around 7% based on the mean value of $Spread$ ($0.139/2.084 = 0.067$).

Besides, bond maturity (MAT) and debt-to-asset ratio (Lev) exhibit significantly positive relationships with credit spreads. This finding is expected as longer maturities and higher leverage increase credit risk, prompting investors to demand higher risk premia to offset potential default concerns. Meanwhile, issuance amount (BI), credit rating ($RATE$), return on assets (ROA), cash flow (CF), liquid ratio ($Liquid$), and the largest shareholder's ownership ($Top1$) exhibit significant negative relationships with credit spreads. A larger BI often suggests greater corporate credibility and financing strength, resulting in a lower risk premium. Similarly, a higher $RATE$ indicates a reduced default risk, which lowers the spread. Companies with higher ROA tend to demonstrate robust profitability, improving their capacity to meet debt obligations, thereby leading to lower spreads. A strong CF suggests that the firm has sufficient resources to manage its debts, minimizing default risk. Additionally, a higher *Liquid* ratio signals stronger short-term liquidity, further diminishing investor risk perceptions. Finally, an increase in $Top1$ generally reflects sound corporate governance, which ensures effective oversight and risk management, thereby reducing the yields investors require for the firm's bonds.

[Table 3 about here.]

4.2 Instrument variables

Our benchmark regressions identified a significant and positive relation between CPU and corporate bond spreads. We address potential endogeneity issues to verify their causal relationship. Although *Spread* are less likely to influence $CPUdivstd$, this possibility cannot be completely excluded. Specifically, an increase in credit spreads may affect CPU, leading to a correlation between the independent variable and error term, thus introducing reverse causality. For instance, rising spreads may place greater operational pressure on firms, prompting the government to frequently adjust the implementation of climate policies to alleviate economic strain, which in turn increases the CPU faced by firms. Another endogeneity issue may arise from unobservable variables that simultaneously affect both CPU and spreads. For instance, managerial quality can be such a factor. High-quality management teams are typically better equipped to handle external policy changes, reducing the CPU risk the firm faces. Furthermore, they may secure financing at lower costs, narrowing the bond spreads. Conversely, firms with weaker management may struggle to cope with policy uncertainty, potentially resulting in higher spreads on their bond issuances.

To address the aforementioned endogeneity issues, we construct three instrumental variables (IV) using the two-stage least squares (IV-2SLS) approach. First, $MeanCPU$ is adopted. It is the average CPU of other firms in the same city and industry, excluding the bond-issuing firm. Firms in the same province and industry face similar regulatory environments. Hence, $MeanCPU$ captures external policy shocks while excluding firm-specific influences. The second IV is *LagCPU*, the firm's one-period lagged $CPUdivstd$. Since firms cannot quickly adjust to climate risks, past CPU affects current conditions, making *LagCPU* a suitable IV. Third, we use the Bartik IV design through the shift-share IV (SSIV) method following Adao et al. (2019) and Borusyak et al. (2022). The *Shift* component reflects industry-wide CPU shocks, while the *Share* component is based on the 2007 provincial CO_2 emission shares by industry. Together, these are used to create a province-level instrument, $SSIV$. The CO_2 data are collected from China Emission Accounts and Datasets (CEADs). The rationale behind constructing this IV is that, at the start of the sample period, the awareness of climate risks was low. Hence, the 2007 emission shares were relatively exogenous to future policies. The *Shift* component reflects industry-level uncertainty and is exogenous from the firm's perspective, capturing the external policy shocks. Since our sample comprises publicly listed firms, which are often the focus of local policy, *SSIV* is closely tied to the firm's CPU, ensuring instrument relevance and exogeneity.[7]

Table 4 presents the IV-2SLS estimation results, with control variables and fixed effects included to account for unobserved heterogeneity across firms, industries, and time. Columns (1), (3), and (5) report the first-stage results. The estimated coefficients for *MeanIV*, *LagIV*, and *SSIV* are all significantly positive, demonstrating that the chosen instruments strongly correlate with the endogenous variable, thereby satisfying the relevance condition of valid instruments. The second stage results in columns (2), (4), and (6) show that the coefficients for $CPUdivstd$ remain positive and statistically significant, even after accounting for potential endogeneity. Thus, our baseline regression results are robust and that CPU has a consistent positive impact on corporate bond spreads. Furthermore, the Kleibergen-Paap rk Wald F-statistics are all well above the critical value of 10, suggesting that the instruments used are not weak. This strengthens the credibility of our IV-2SLS estimates, demonstrating that the instruments effectively mitigate the possible endogeneity concerns present in the baseline estimates.

[Table 4 about here.]

4.3 Difference-in-difference approach

The DID approach is another effective method for addressing endogeneity issues. By comparing the evolution of outcomes over time between treatment and control groups, it controls for unobserved factors that may bias the estimation results. Following Seltzer et al. (2022) and Cheng et al. (2024), we take the Paris Agreement in December 2015 as a quasi-natural experiment, which can be regarded as an exogenous CPU shock. On the one hand, this global event, determined through international negotiation rather than by any single nation's decision, is external to Chinese firms. On the other hand, the Paris Agreement permits each participating country to set its emission reduction targets based on specific circumstances. While this flexibility facilitates global cooperation, it simultaneously introduces policy uncertainty. This is because, although the signing of the agreement clarified countries' emission reduction commitments, enterprises face numerous uncertainties regarding the specific policy formulation and implementation details. For instance, they are uncertain about which specific emission reduction policies will be introduced in the future, the compliance requirements, and the implementation timelines. This increases their concerns about the future policy environment, thereby increasing CPU. Furthermore, specific targets and even commitments to the agreement itself can change due to political shifts, conflicts among stakeholders, the development of new technologies, and macroeconomic fluctuations (Kriegler et al., 2015; Gavriilidis, 2021; Ren et

[7] Appendix D elaborates how we use the *Shift* (industry-level CPU shock) and *Share* (provincial CO_2 emissions share) components to construct *SSIV*.

al., 2023). Therefore, the signing of the Paris Agreement serves as a good proxy for an exogenous shock to the CPU.

We define the treatment group by identifying high-energy consumption and high-emission firms most exposed to climate policy risks. Following the 2021 guidelines issued by the Chinese Ministry of Ecology and Environment, titled *Guiding Opinions on Strengthening the Prevention and Control of High Energy Consumption and High Emission Construction Projects from the Source*, we classify the "two-high" industries, which include coal power, petrochemicals, chemicals, steel, non-ferrous metal smelting, and building materials (Wang, 2023b).[8] Bonds issued by firms in these industries are considered part of the treatment group.

$$Spread_{it} = \alpha + \theta_1 Treat_j \times Post_t + \theta_2 BondControls_{it} + \theta_3 IssuerControls_{j,t-1} + \lambda_j + \lambda_t + + \varepsilon_{ijt} \quad (6)$$

where $Treat$ equals one for the treatment group. $Post$ equals zero before 2015; and one otherwise.

$$Post_t = \begin{cases} 0, & \text{if } t < 2015 \\ 1, & \text{if } t \geq 2015 \end{cases} \quad (7)$$

Table 5 presents the results from Equation (6). In column (1), we include year and firm fixed effects, while column (2) adds control variables to the model. the interaction term ($Treat \times Post$) exhibits a significant positive effect at the 5% level. Thus, bonds issued by high-emission and high-energy-consuming firms experience increased spreads relative to those issued by lower-emission firms after China signed the Paris Agreement. This suggests that the market demands higher returns for holding bonds from higher-emission firms due to the increased regulatory risks associated with climate change.

[Table 5 about here.]

The effectiveness of the DID approach is heavily dependent on fulfilling the parallel trends assumption. Specifically, for this assumption to hold, in the absence of treatment, the bond spreads of treatment group firms will not significantly differ from those in the control group. To test this assumption, we follow the methodology used by Li et al. (2020) and Fang et al. (2017) and estimate the regression based on Equation (8).

$$\begin{aligned} Spread_{it} = \alpha + \sum_{k=-5}^{-1} \beta_k \cdot Treat_j \times I(t=k) + \sum_{k=0}^{5} \gamma_k \cdot Treat_j \times I(t=k) \\ + \theta_2 BondControls_{it} + \theta_3 IssuerControls1_{j,t-1} + \lambda_j + \lambda_t + \varepsilon_{ijt} \end{aligned} \quad (8)$$

[8] The document is available at https://www.mee.gov.cn/xxgk2018/xxgk/xxgk03/202105/t20210531_835511.html (in Chinese).

where $I(t=k)$ is an indicator variable that equals 1 if time t corresponds to the relative period k. For example, $I(t=-2)$ represents two years before the event, while $t=-5$ indicates the fifth year before or earlier. β_k represents the interaction terms for pre-treatment periods, which are used to test the parallel trends assumption, and γ_k captures the treatment effects post-event implementation.

Figure 4 illustrates the pre-treatment trends between the treatment and control groups. The points represent the estimated coefficients of β_k and γ_k, accompanied by their corresponding 95% confidence intervals. Notably, the interaction terms between the treatment variable and relative time before the Paris Agreement are all close to zero and statistically insignificant. Thus, the treatment and control groups do not have significantly different trends before the event, thereby supporting the parallel trends assumption. Additionally, after the Paris Agreement, the interaction terms become significantly positive at $t=1$ and $t=2$. This suggests that bonds issued by high-emission firms begin experiencing increased spreads relative to lower-emission firms during these periods. However, at $t=0$, the interaction term is not statistically significant, indicating that the immediate impact following the agreement was not evident. This delayed response may suggest that financial markets took time to fully incorporate the increased regulatory risks associated with climate policies into bond pricing.

Moreover, after $t=3$, the impact of the Paris Agreement's policy shock on bond spreads gradually diminishes and becomes statistically insignificant. Thus, the initial market reaction to the regulatory risks associated with climate policies was concentrated in the early periods following the agreement; however, over time, this effect dissipated. One possible explanation is that more detailed provisions were introduced gradually. This allowed the market to gain greater clarity over time, stabilizing bond spreads for firms with higher emissions.

Overall, these results support the parallel trends assumption and demonstrate that CPU significantly increased bond spreads for high-emission firms, with this effect tapering off as additional policies were introduced and uncertainty was progressively reduced.

[Figure 3 about here.]

4.4 Other robustness checks

Sample selection bias: To account for potential sample selection bias, we apply the Heckman two-step method (Lennox et al., 2012). This approach helps address the possibility that our sample may not be randomly selected, which could lead to biased estimates. In the first stage, we estimate a selection equation using a probit model to determine a firm's likelihood of issuing bonds based on various firm characteristics. The resulting inverse Mills ratio (IMR; *MILLS*) is then incorporated into the second stage, where we re-estimate the impact of $CPUdivstd$ on $Spread$. Including the IMR helps control for the non-random selection process, ensuring that our estimates of the CPU effects on credit spreads are unbiased and consistent.

$$Pr(bond_{jt}=1)=\Phi(\gamma Z_{jt})=\theta_0+\theta_1 IssuerControls_{j,t-2}+\theta_2 IssuerControls_{j,t-1}+\lambda_j+\lambda_t+\varepsilon_{ijt} \tag{9}$$

$$\begin{aligned} Spread_{ijt} =& \alpha+\beta_1 CPUdivstd_{jt}+\beta_2 BondControls_{ijt}+\beta_3 IssuerControls_{j,t-1} \\ &+\rho\sigma\hat{\lambda}(\gamma Z_{jt})++\lambda_j+\lambda_t+\varepsilon_{ijt} \end{aligned} \tag{10}$$

[Table 6 about here.]

Specifically, in the first stage selection model (Equation (9)), the dependent variable is a binary indicator where *bond* equals 1 if firm j issued a bond in year t (i.e., entered our sample), and 0 otherwise. We estimate this using a probit model. In the second stage (Equation (10)), we incorporate the IMR (*MILLS*) into the baseline regression model to account for sample selection bias. In column (1), no exclusion restriction is applied. An exclusion restriction refers to the inclusion of variables in the selection model, which influence the probability of an observation being included in the sample but do not directly affect the outcome variable (Lennox et al., 2012). In column (2) of Table 6, we introduce an exclusion restriction by including lagged firm-level controls ($IssuerControls_{j,t-2}$): the two-period lagged values of ROA, cash flow ratio, leverage, and liquidity ratio. These lagged financial indicators are closely linked to a firm's decision to issue bonds, making them suitable as exclusion variables in the selection model. Table 6 indicates that, regardless of exclusion restrictions, the variance inflation factor values for *MILLS* remain below 10, suggesting no severe multicollinearity issues. While *MILLS* is statistically significant and positive in column (2), the coefficient for $CPUdivstd$ remains positive and comparable to the baseline regression (Table 3). Therefore, even after controlling for potential sample selection bias, CPU continues to increase bond spreads; overall, our results are robust.

Aggregated results: In the benchmark analysis, we use the "bond-year" as one observation. To smooth out idiosyncratic fluctuations and focus on the general pattern, we aggregate data to the firm level, where each observation represents the average characteristics of bonds issued by a particular firm j within a given year t. Particularly, the explained variable, $SpreadEVE_{jt}$, is the average credit spreads of bonds issued by firm j in period t. The bond-level control variables, $BondControlsEVE_{jt}$, are calculated as average bond issuance BI and maturity MAT, as well as the median for the rating $RATE$, and dummy variables RDM and PUT. The regression is expressed as follows.

$$SpreadEVE_{jt}=\alpha+\beta_1 CPUdivstd_{jt}+\beta_2 BondControlsEVE_{jt}+\beta_3 IssuerControls_{j,t-1}+\lambda_j+\lambda_t+\varepsilon_{jt} \tag{11}$$

Table 7 shows the estimated results of Equation (11). The coefficient for $CPUdivstd$ is positive and significant at the 5% level. After including control variables and fixed effects, as shown in column (2), the coefficient closely aligns with the baseline regressions in Table 3. This validates our finding that firms facing higher climate policy risks are likely to increase their credit spread to facilitate financing.

[Table 7 about here.]

Alternative CPU measures: To ensure that our results are not dependent on a specific measure of the key variable, we use two macro-level CPU measures for robustness checks. The first is constructed following Gavriilidis (2021), and the other is from Lee and Cho (2023). The former metric measures CPU in the US (denoted as $USACPU$), while the latter is a Twitter-based gauge of China's CPU (referred to as $TCCPU$). Since both variables are macro-level and remain the same for all firms, we do not include time-fixed effects. Instead, we incorporate market control variables such as the EPU Index, and GDP and money supply (M2) growth rates.

$$\begin{aligned} Spread_{ijt} =& \alpha + \beta_1 TCCPU_t(USACPU_t) + \beta_2 BondControls_{ijt} + \beta_3 IssuerControls_{j,t-1} \\ &+ \beta_4 MarketControls_t + \lambda_j + \varepsilon_{ijt} \end{aligned} \tag{12}$$

As shown in Table 8, we include firm fixed effects, and firm- and bond-level control variables in all regressions. We add market control variables in columns (2) and (4). Columns (1) and (2) use $TCCPU$ to measure CPU, while columns (3) and (4) use $USACPU$. The estimated coefficients for CPU are significantly positive in columns (1)–(3). In column (4), the coefficient is positive but not statistically significant, with a t-value of 1.6 which is close to the 10% significance level. Although climate risk is a global concern, one may reasonably expect that China's financial markets are more sensitive to domestic CPU. This aligns with the fact that domestic policies often have a more direct and immediate impact on firms' operating environments and financial conditions. Hence, the stronger reaction to $TCCPU$ compared to $USACPU$ is consistent with the expectation.[9]

[Table 8 about here.]

4.5 Cross-sectional heterogeneity

Green versus conventional bonds: Table 9 presents the differential responses of *Spread* between green and conventional bonds to CPU. Green bonds are debt instruments issued to finance projects that meet specific environmental protection or sustainable development criteria.[10] According to Zerbib (2019) and Dorfleitner et al. (2021), green bonds typically trade at lower yields compared to their conventional counterparts. This suggests that investors are willing to accept slightly

[9] In Table F.1, we report the robustness checks by adding fixed effects, adjusting the standard errors for clustering at different levels, and excluding the COVID-19 observations.

[10] In 2015, the People's Bank of China published the Green Bond Endorsed Project Catalog, which provided clear guidance on the use of proceeds for green bonds. This laid the foundation for the subsequent development of China's green bond market.

lower returns in exchange for contributing to environmental benefits. This phenomenon, known as a "greenium", reflects the market's recognition of environmentally responsible investing. Following Wang et al. (2020), we use the green flag provided by the CSMAR database to identify whether a bond is classified as a green bond.

In Table 9, columns (1) and (2) report the regression results for the green and conventional bond sub-samples, respectively. In column (1), the estimated coefficient of $CPUdivstd$ is significantly negative. In column (2), the estimated coefficient of $CPUdivstd$ is significantly positive. Column (3) presents the regression results for the entire sample, showing that the coefficient of $CPUdivstd \times Green = 1(ConventionalBonds)$ remains significantly positive, and the joint coefficient test between green and conventional bonds yields a p value less than 0.05. Thus, the response of credit spreads to CPU is significantly different between the two types of bonds at the 5% significance level. This difference hints that green bonds exhibit greater resilience to CPU, potentially due to the environmental nature of their funding and investors' long-term commitment to environmental responsibility. This mitigates the negative impact of CPU risks. Overall, this finding supports the unique advantages of green financial instruments in addressing environmental risks.

[Table 9 about here.]

Maturity: Table 10 presents the results by bond maturities. Specifically, we segment our sample by the issuance period, which is the time span from the bond's issue date to its initial maturity date, into short- to medium- (first quartile, $< p25$, 5 years), and long-term bonds (last quartile, $> p75$, 7 years), as shown in columns (1) to (2), respectively. The findings in Table 10 reveal an intriguing pattern: Compared to long-term bonds, the estimation coefficients of $CPUdivstd$ for the short- to medium-term bond group are significantly higher. The penultimate row of Table 10 displays the t-test for the coefficient difference of $CPUdivstd$ between columns (1) and (2). The p-value is less than 0.1. The final row shows the joint coefficient test for column (3) between $CPUdivstd \times Maturity < p25$ and $CPUdivstd \times Maturity > p75$, with p-values also less than 0.10. This indicates a variance in bond spread's responsiveness to CPU across different issuance maturities, with a more pronounced effect in short- to medium-term bonds.

Ivanov et al. (2023) found that after implementing the emission trading policy, firms with higher greenhouse gas emissions faced shorter loan durations and higher interest rates. Lin and Li (2022) investigated how EPU affects strategic investments between Chinese renewable energy companies, discovering that the expectations of the capital market are not significantly influenced by EPU; this indicates a minor long-term impact of this uncertainty on strategic investments by renewable energy firms. Our results echo these findings, highlighting a heightened market sensitivity to the short-term impacts of CPU. This sensitivity reflects investors' acute awareness of immediate policy shifts and market fluctuations, leading to a demand for higher risk premia in the face of CPU. However, investors perceive that firms have ample time to adapt to CPU for long-term bonds.

[Table 10 about here.]

Ownership: Table 11 differentiates the sample based on the issuer's ownership, distinguishing between state-owned enterprises (SOEs) and non-SOEs. The estimated coefficients in columns (1) and (2) show significant differences, with non-SOEs' credit spreads more influenced by $CPUdivstd$. This pattern is consistent in the full sample regression shown in column (3) that the p-value of joint test is less than 0.05. This finding aligns with the notion that SOEs and non-SOEs exhibit distinct behaviors in the face of policy risks. SOEs benefit from privileged access to insider information regarding policy shifts and are subject to fewer financial restrictions owing to governmental credit support, which reduces their risk of financial distress (Dong et al., 2021; Cao et al., 2022). Consequently, the investors' apprehension regarding uncertainty is substantially lower for SOEs than for firms within the private sector.

[Table 11 about here.]

Supply chain concentration: In Table 12, we use the mean ratio of the top five suppliers' and customers' procurement and sales to measure supply chain concentration. A higher concentration indicates stronger dependence on a few suppliers and customers. Based on this metric, we divide the sample into two groups: low (LSP, column (1)) and high supply chain concentration (HSP, column (2)). Our results show that in the LSP group, the relationship between $CPUdivstd$ and *Spread* is significantly positive. Thus, as the uncertainty increases, corporate credit risk premium rises. In contrast, the coefficient remains positive but insignificant in the HSP group. Column (3) introduces an interaction term between the supply chain dummy (*SupplyChain*) and $CPUdivstd$, with a joint significance test p-value of 0.006. Thus, the response of *Spread* to CPU varies significantly.

This finding is contrary to the general belief that supply chain diversity can effectively mitigate operational risk. Our results suggest that firms with lower supply chain concentration may face increased management and operational uncertainty due to supply chain complexity when responding to CPU. Indeed, Upson and Wei (2024) found that although supply chain diversification theoretically reduces risk, this effect can be offset by the increased complexity and management difficulty, potentially exposing firms to greater uncertainty and financial risk. In other words, for firms with more diversified supply chains, the combination of supply chain complexity and CPU may exacerbate credit risk premium.

[Table 12 about here.]

5 Further Analyses

5.1 Financial distress

A firm under financial distress may experience reduced debt repayment capacity, balance sheet deterioration, and a loss of market confidence (D'Mello and Toscano, 2020). Thus, as the severity of financial distress increases, the firm finds it increasingly difficult to access low-cost financing in debt markets as investors begin to question the firm's ability to repay its debts and, in turn, demand higher risk premiums. However, the CPU also plays a significant role in exacerbating corporate financial distress. As countries implement increasingly stringent climate policies, companies, especially those in high-carbon industries, face mounting pressure from governments, the public, and investors. When CPU rises, firms may navigate an unpredictable regulatory environment that heightens compliance and legal risks, thereby increasing the likelihood of financial distress. Additionally, CPU can dampen corporate investment, particularly in long-term projects. Specifically, this uncertainty makes it difficult for firms to plan for the future, leading to delayed or reduced capital expenditures. This ultimately impacts the company's financial stability and long-term sustainability, and further elevates the risk of financial distress. Hence, financial distress can be considered as a mechanism through which CPU impacts bond credit spreads, as assumed by **Hypothesis 2**.

The Altman Z-Score model (Altman, 1968) is a widely used tool for predicting corporate financial distress (Almamy et al., 2016). This model integrates various financial ratios, including profitability, leverage, liquidity, and activity, to effectively assess a firm's financial health. Following Ji et al. (2022) and Ding et al. (2023), we use it to measure corporate financial distress, denoted as *Zscore*. The higher the Z-Score, the lower the firm's risk of bankruptcy (i.e., the lower the financial distress). Appendix E provides a detailed explanation of the Z-Score calculation method.

To mitigate the potential interference from endogeneity in the mechanism variable during the analysis, we follow the approach of Alesina and Zhuravskaya (2011) and Persico et al. (2004) for conducting mechanism tests. These sets of authors discussed how a mediating variable can transmit the effect of a treatment variable to the outcome variable. They concluded that the mediating channel remains valid as long as the relationship between the mediator and outcome variable is well-established, and including the mediator as a control variable alters the coefficient of the treatment variable either in magnitude or significance. Similar approaches have been employed by Bukari et al. (2024), Churchill and Smyth (2022), and Xu (2022).

Based on these studies, to test **Hypothesis 2**, we use the one-period lag of the mediating variable financial distress, denoted as $Zscore_{j,t-1}$, and propose two regression models:

$$Spread_{ijt} = \alpha + \rho Zscore_{j,t-1} + \beta_2 BondControls_{ijt} + \beta_3 IssuerControls_{j,t-1} + \lambda_j + \lambda_t + \varepsilon_{ijt} \quad (13)$$

$$
\begin{aligned}
Spread_{ijt} = & \alpha + \rho Zscore_{j,t-1} + \beta_1 CPUdivstd_{jt} + \beta_2 BondControls_{ijt} \\
& + \beta_3 IssuerControls_{j,t-1} + \lambda_j + \lambda_t + \varepsilon_{ijt}
\end{aligned}
\tag{14}
$$

Specifically, in the first step, we reference the literature to establish that financial distress, as a potential mediating variable, impacts the credit spread. That is, the smaller the *Zscore* (indicating more severe financial distress), the larger the credit spread. We demonstrate the relationship between *Spread* and *Zscore* through both a group mean comparison test and regression analysis. Table 13a presents the T-test results based on groups divided by the thresholds 1.81 and 2.67, while Table 13b shows the results using the top and bottom quartiles.[11] In both tables, as the *Zscore* decreases, the bond spread increases, with significant differences at the 1% level. The regression results of *Spread* on *Zscore* (Equation (13)) are presented in column (1) of Table 13c. The estimated coefficient of *Zscore* is significantly negative, indicating that bond spreads decrease when a firm's financial condition improves.

In the second step, we include the *Zscore* in the baseline regression, estimating Equation (14), with the results shown in column (2) of Table 13c. For comparison, we also incorporate the results from column (3) of Table 3 into column (3) of Table 13c. After including the *Zscore*, the estimated coefficient for *CPUdivstd* decreases. Further, the *t*-statistic also slightly diminishes, although it remains significant at the 5% level. Thus, financial distress serves as a channel through which CPU affects bond spreads.

[Table 13 about here.]

5.2 ESG disclosure

As stated by **Hypothesis 3a**, firms demonstrating better adaptability to climate policies and proactive environmental governance (a higher ESG) will likely be favored, enjoying lower spreads on their bonds. Conversely, firms that neglect the impact of climate change and lack appropriate adaptation measures may face aversion from investors, thereby increasing their bond spreads. Meanwhile, since corporate ESG is currently rated by multiple agencies, their disagreement may make the situation worsen according to **Hypothesis 3a**.

The Chinese market has six ESG rating systems administered by different entities. Here, those by *FTSE* and *Bloomberg* represent international agencies, whereas *SSI*, *SuallWave*, *SynTao*, and *Wind* are domestic (Wang et al., 2024b). Wang et al. (2024a) noted that divergences in ESG ratings can elevate the costs associated with information processing, possibly shifting investor focus away from ESG considerations or inducing greater caution in their reliance on such ratings. Furthermore, Avramov et al. (2022) observed that ESG rating uncertainties dampen stock demand and that brown

[11] Using 1.81 as a threshold, firms with a Z-Score greater than 2.67 are considered to be in good financial health, with a low likelihood of bankruptcy. Firms with a Z-Score less than 1.81 are considered to be in financial distress, facing a significant risk of bankruptcy (Altman, 1968; Pryshchepa et al., 2013).

stocks only outperform green stocks under low rating uncertainty. Therefore, to examine **Hypotheses 3a** and **3b**, we add the interaction terms $CPUdivstd \times ESGscore$ and $CPUdivstd \times ESGgap$, receptively.

[Table 14 about here.]

We use *ESGscore* to represent the ESG rating value. The ESG ratings provided by *Wind*, *SSI*, *SynTao*, and *SuallWave* have been linearized for this analysis. Furthermore, *ESGgap* refers to the ESG disagreement, calculated in accordance with the methodology outlined by Avramov et al. (2022). Table 14 reports the impact of ESG ratings and ESG disagreement on the relationship between CPU and bond spreads. Columns (1)–(6) use ESG scores from different agencies. The estimated coefficient for $CPUdivstd \times ESGscore$ is negative across all specifications. In columns (3) and (6), the coefficients are significant at the 5% level. Meanwhile, they are significant at the 10% level in columns (1), (2), and (4). This suggests that corporate ESG disclosure can mitigate the impact of CPU on bond spreads. Specifically, the more comprehensive a firm's ESG practices, the more effectively it can alleviate the influence of CPU on its debt financing. In contrast, the estimated coefficient for $CPUdivstd \times ESGgap$ in column (7) is positive and significant at the 5% level. This implies that ESG rating discrepancies actually exacerbate the increase in credit spreads caused by CPU.

5.3 Credit rating and bond issuance amount

We further examine the impact of CPU on bond ratings and issuance volumes. Regression models are developed to analyze these relationships, with detailed model specifications and results presented in Table G.1 of Appendix G. Overall, CPU has a small but significant negative effect on credit ratings. This indicates that rating agencies do consider CPU, but that this impact is relatively minor, accounting for only about 1% of the average rating value. Regarding bond issuance volumes, we find no significant effect of CPU. This suggests that, on average, firms have neither postponed nor accelerated their bond financing due to CPU impacts.

6 Conclusion

This study reveals CPU's significant impact on corporate bond credit spreads in China's bond market. By leveraging LLMs to construct a firm-level CPU index from corporate disclosures (i.e., CSR), MD&A, and ECCs, we provide a novel approach to quantifying CPU at the firm level. We find that increased CPU leads to wider credit spreads for firms, indicating higher financing costs associated with climate policy risks.

Our results have significant implications from a policy perspective. The observed relationship between CPU and higher credit spreads highlights a critical chain of effects: CPU increases the likelihood of financial distress, thereby widening corporate credit spreads. This mechanism underscores the need for more consistent and transparent climate policies. Frequent policy changes and unclear long-term commitments increase CPU, which exacerbates the risk of financial distress. This increased risk is reflected in higher credit spreads, effectively raising firms' cost of capital. Consequently, this may discourage investment in sustainable initiatives, as companies become more cautious in their financial decisions when facing potential distress. Policymakers should strive to reduce uncertainty by formulating long-term, stable, and clear climate strategies. Such an approach can mitigate the risk of financial distress stemming from policy uncertainty, thereby improving firms' access to bond financing at more favorable terms. This can not only help firms in their planning and investment decisions but also support the broader goal of transitioning to a low-carbon economy by reducing the financial barriers to sustainable investments.

We also highlight the critical role of ESG performance in mitigating the adverse effects of CPU. Specifically, firms with higher ESG ratings experience a less significant impact of CPU on their credit spreads, suggesting that strong ESG practices improve resilience against policy uncertainties. However, ESG rating divergences amplify the negative effects, indicating the need for standardization in ESG evaluations. Regulators and industry bodies should consider establishing unified ESG reporting standards to reduce discrepancies among rating agencies, thereby providing clearer signals to investors and reducing the cost of capital for firms committed to sustainable practices.

Finally, the heterogeneity of CPU's impact across different types of bonds and firms suggests that policy interventions can be more targeted. For instance, supporting non-SOEs and firms with dispersed supply chains in managing CPU may require offering incentives for green bond issuance or providing access to resources that help them adapt to changing climate policies.

As China and other nations continue to grapple with climate change challenges, addressing the implications of CPU becomes increasingly vital. By promoting policy consistency, improving ESG standards, and integrating CPU into financial risk assessments, policymakers, firms, and investors can collectively reduce the financial vulnerabilities associated with CPUs. Such efforts will not only improve market efficiency but also contribute to sustainable economic development and the global fight against climate change.

Figures

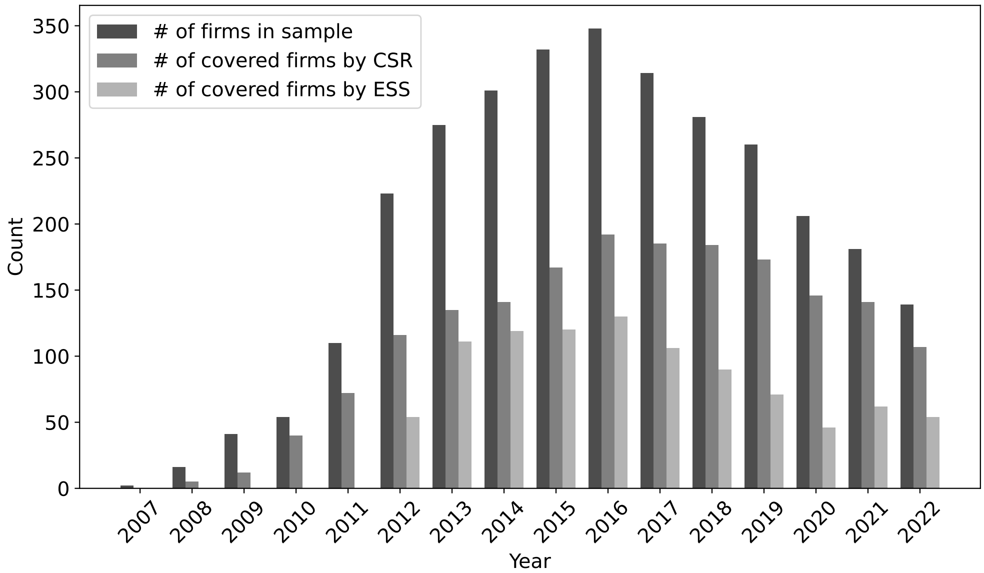

Figure 1. Annual Coverage of Firms by CSR and ECC

Note: *This figure illustrates the coverage of three types of information disclosure among sample firms for each year. All firms have MD&A, while some disclose CSR reports and hold ECC. For example, in 2012, our sample has 223 firms, among which 223 firms have MD&A, 116 firms have CSR and 54 firms have ECC.*

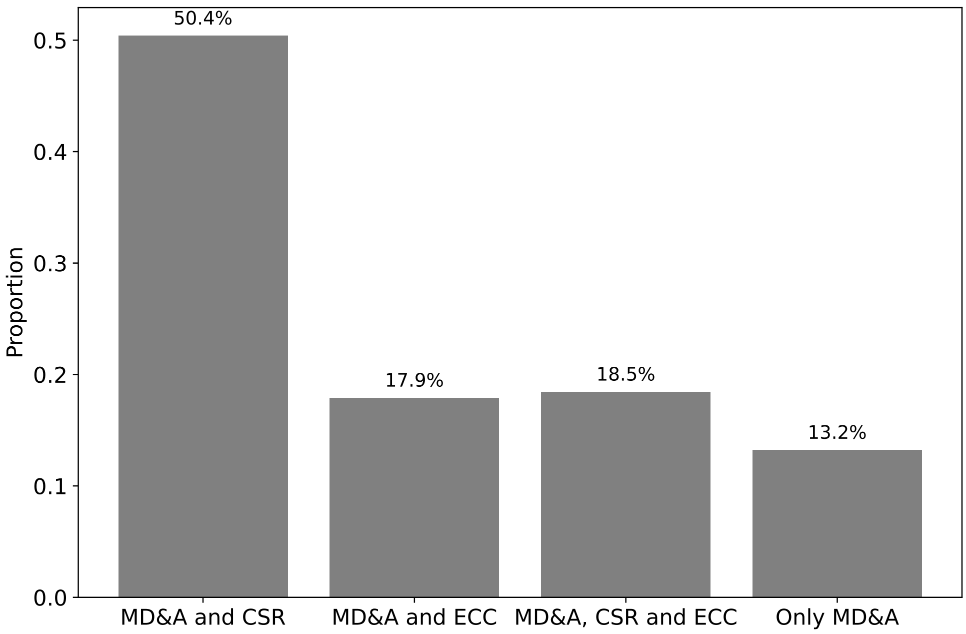

Figure 2. Total Coverage of Observations by MD&A, CSR and ECC

Note: *This figure depicts the total coverage of observations across different combinations of MD&A, CSR and ECC. The bar chart presents four distinct categories of reporting combinations. For example, the first bar represents the percentage of observations that are covered by only MD&A and CSR is 50.4%.*

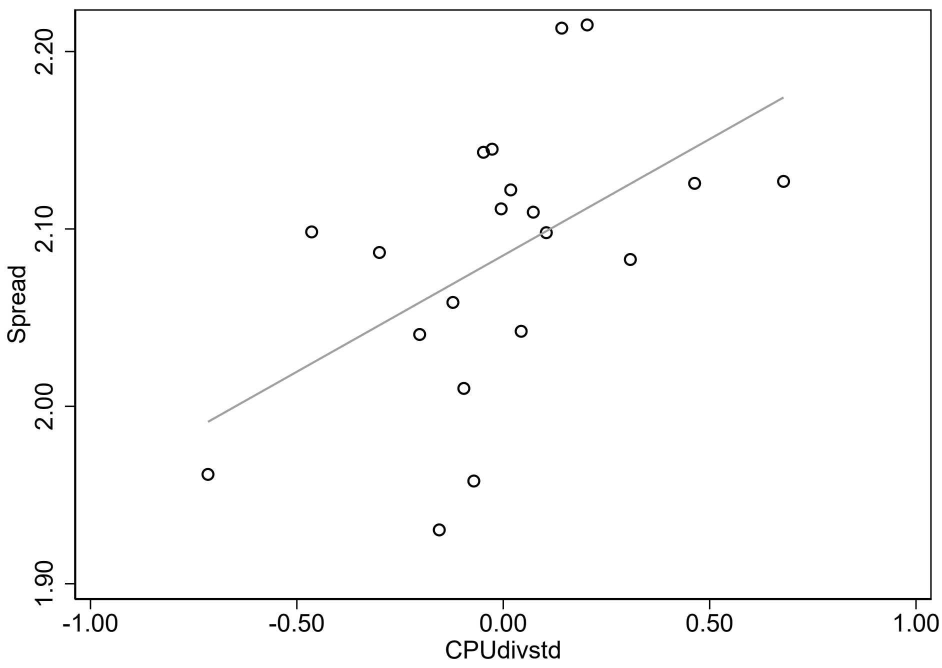

Figure 3. Binned Scatterplots of *Spread* vs. *CPUdivstd*

Note: *This figure presents binned scatterplots illustrating the relationship between the spread (y-axis) and CPUdivstd (x-axis). Each point represents a representative sample point, reflecting the average values within bins of the CPUdivstd variable. The solid line represents the fitted trend line after controlling for both time and firm fixed effects*

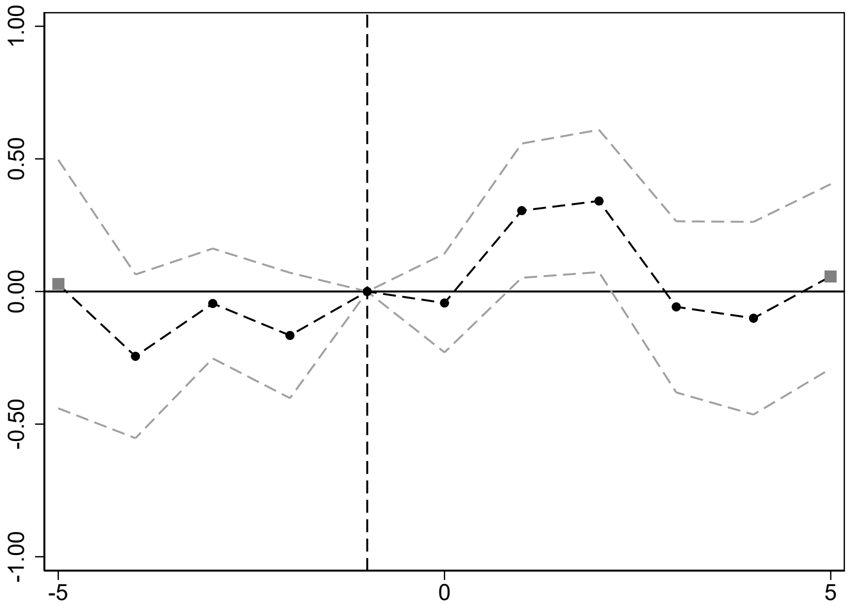

Figure 4. Parallel Trend Hypothesis Test

Note: *The x-axis shows the relative time before and after the Paris Agreement, with $t = 0$ marking the year 2015. Periods before $t = -5$ and after $t = +5$ are grouped into a final bin, represented by square markers. The dots represent the estimated coefficients of β_k and γ_k from Equation* (8)*, with the dashed lines above and below indicating the 95% confidence intervals.*

Tables

Table 1. Variable Definitions

Variables	Descriptions
Dependent variable	
Spread	Credit spread (unit: %) of each bond calculated by Equation (2)
Independent variable	
CPUdivstd	Firm-level climate policy uncertainty
Control variables: *bond*	
BI	(*log*) Bond issuance amount (unit: CNY 100M)
MAT	(*log*) Bond maturity (unit: Y) between issue data and maturity expressed in years
RATE	Credit rating that is linearized and ranges from 1 (A+) to 5 (AAA)
RDM	Variable equals to 1 if the bond is callable, and 0 otherwise
PUT	Variable equals to 1 if the bond is putable, and 0 otherwise
Control variables: *issuer*	
Size	(*log*) Firm's asset
Age	(*log*) Firm age
ROA	Return on assets
FIXED	Fixed assets ratio
CR	The ratio of operating cash flow to current liabilities
Lev	Debt-to-assets ratio
Liquid	The ratio of current assets to current liabilities
*Top*1	Proportion of the largest shareholder (unit: %)
INST	Proportion of institutional holders (unit: %)

Table 2. Descriptive Statistics

	Obs.	Mean	SD	Min	$p50$	Max
$Spread$	4,959	2.084	1.368	0.152	1.772	6.641
$CPUdivstd$	4,959	-0.009	0.962	-1.042	-0.341	3.618
BI	4,959	2.331	0.779	0.470	2.303	4.248
MAT	4,959	1.663	0.317	1.099	1.609	2.303
$RATE$	4,959	4.159	0.856	3.000	4.000	5.000
RDM	4,959	0.059	0.236	0.000	0.000	1.000
PUT	4,959	0.674	0.469	0.000	1.000	1.000
$Size$	4,959	24.384	1.663	21.293	24.172	28.504
Age	4,959	2.927	0.350	1.792	2.996	3.555
ROA	4,959	0.034	0.033	-0.068	0.029	0.153
$FIXED$	4,959	0.246	0.217	0.002	0.191	0.793
CF	4,959	0.035	0.067	-0.224	0.040	0.191
Lev	4,959	0.601	0.150	0.225	0.613	0.866
$Liquid$	4,959	1.355	0.836	0.197	1.197	5.300
$Top1$	4,959	40.080	16.266	7.823	39.961	82.553
$INST$	4,959	63.202	21.982	4.385	66.705	106.738

Note: *Variables are winsorized at 1% and 99%. The definitions of variables are listed in Table 1.*

Table 3. Benchmark Regression Results

	(1) Spread	(2) Spread	(3) Spread
CPUdivstd	0.131***	0.138**	0.145**
	(3.525)	(3.131)	(3.298)
BI		-0.073*	-0.074*
		(-1.888)	(-1.961)
MAT		0.193**	0.185**
		(2.215)	(2.237)
RATE		-0.254**	-0.256**
		(-2.605)	(-2.794)
RDM		0.006	0.025
		(0.043)	(0.186)
PUT		-0.069	-0.075
		(-0.881)	(-0.981)
Size			0.018
			(0.163)
Age			-0.687
			(-1.625)
ROA			-4.239***
			(-5.251)
FIXED			0.133
			(0.396)
CF			-0.622**
			(-2.279)
Lev			0.902**
			(2.216)
Liquid			-0.114**
			(-2.847)
*Top*1			-0.011**
			(-2.072)
INST			-0.000
			(-0.071)
Constant	2.085***	3.036***	4.838*
	(185.709)	(7.054)	(1.696)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Adj R-squared	0.666	0.670	0.683
Obs.	4,959	4,959	4,959

Note: *The values in parentheses are t-statistics. Standard errors are clustered at the firm level. We report significance levels as follows:* $* \, p < 0.10$, $** \, p < 0.05$, $*** p < 0.001$.

Table 4. IV-2SLS Regression Results

	IV: MeanCPU		IV: LagIV		IV: SSIV	
	(1) First	(2) Second	(3) First	(4) Second	(5) First	(6) Second
CPUdivstd		0.231**		0.294***		0.796*
		(2.844)		(4.117)		(1.658)
MeanIV	0.786***					
	(11.037)					
LagIV			0.335***			
			(12.169)			
SSIV					0.041***	
					(5.122)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F-value		121.813		148.093		26.232
Obs.	4,959	4,959	4,959	4,959	4,959	4,959

Note: *The values in parentheses are t-statistics. Standard errors are clustered at the firm level. We report significance levels as follows:* $* p < 0.10$, $** p < 0.05$, $*** p < 0.001$.

Table 5. DID Results

	(1) Spread	(2) Spread
Treat $\times$ *Post*	0.278^{**}	0.263^{**}
	(2.345)	(2.381)
Controls	No	Yes
Fixed effects	Yes	Yes
Adj R-squared	0.667	0.683
Obs.	4,959	4,959

Note: *The values in parentheses are t-statistics. Standard errors are clustered at the firm level. We report significance levels as follows:* * $p < 0.10$, $**\, p < 0.05$, $***p < 0.001$.

Table 6. Robust Check: Heckman Two-Step Method

	(1) Spread	(2) Spread
CPUdivstd	0.140**	0.141**
	(3.117)	(3.098)
MILLS	0.476	0.493*
	(1.627)	(1.671)
Variance-Inflation-Factors (VIFs)		
MILLS	6.720	6.60
Controls	Yes	Yes
Fixed effects	Yes	Yes
Exclusion restriction	No	Yes
Adj R-squared	0.683	0.683
Obs.	4,959	4,812

Note: *The values in parentheses are t-statistics. Standard errors are clustered at the firm level. We report significance levels as follows:* $* \, p < 0.10$, $** \, p < 0.05$, $*** p < 0.001$.

Table 7. Robust Check: Aggregated Results

	(1) SpreadEVE	(2) SpreadEVE
CPUdivstd	0.147^{**}	0.155^{**}
	(2.661)	(2.777)
Controls	No	Yes
Fixed effects	Yes	Yes
Adj R-squared	0.680	0.707
Obs.	3,015	3,015

Note: *The values in parentheses are t-statistics. Standard errors are clustered at the firm level. We report significance levels as follows:* * $p < 0.10$, $**\, p < 0.05$, $***p < 0.001$.

Table 8. Robust Check: Alternative Measurements

	CPU: TCCPU		CPU: USACPU	
	(1)	(2)	(3)	(4)
	Spread	Spread	Spread	Spread
TCCPU	0.000**	0.001***		
	(2.758)	(5.206)		
USACPU			0.003***	0.002
			(4.244)	(1.606)
EPU		0.085***		0.057***
		(5.941)		(3.755)
GDP		-0.244		0.062
		(-0.589)		(0.165)
M2		-0.049***		-0.015
		(-4.457)		(-1.426)
Constant	2.758	11.407**	7.017**	8.035**
	(1.227)	(2.752)	(3.201)	(2.089)
Controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No
Adj R-squared	0.630	0.637	0.628	0.630
Obs.	4,894	4,894	4,959	4,959

Note: *The values in parentheses are t-statistics. Standard errors are clustered at the firm level. We report significance levels as follows:* $* p < 0.10$, $** p < 0.05$, $*** p < 0.001$.

Table 9. Heterogeneity From Green and Conventional Bonds

	Sub-groups		All sample
	(1)	(2)	(3)
	Green bonds	Conventional bonds	Both bonds
$CPUdivstd$	-0.324*	0.148***	
	(-1.665)	(3.932)	
$CPUdivstd \times Green = 0(ConventionalBonds)$			0.152***
			(3.415)
$CPUdivstd \times Green = 1(GreenBonds)$			-0.035
			(-0.577)
Adj R-squared	0.770	0.681	0.683
Obs.	194	4,765	4,959
Differences in coefficients across models (p-value)	0.004		
Linear combination test (p-value)			0.001

Note: *All regressions include control variables and fixed effects. The values in parentheses are t-statistics. Standard errors are clustered at the firm level. We report significance levels as follows:* $* \ p < 0.10$, $** \ p < 0.05$, $***p < 0.001$.

Table 10. Heterogeneity From Original Maturity

	Sub-groups		
	(1) Maturity $< p25$	(2) Maturity $> p75$	(3) $< p25$ and $> p75$
$CPUdivstd$	0.232**	0.037	
	(2.594)	(0.438)	
$CPUdivstd \times Maturity = 0(< p25)$			0.198**
			(2.493)
$CPUdivstd \times Maturity = 1(> p75)$			0.053
			(0.851)
Adj R-squared	0.841	0.586	0.751
Obs.	759	615	1,355
Differences in coefficients across models (p-value)		0.084	
Linear combination test (p-value)			0.063

Note: *All regressions include control variables and fixed effects. The values in parentheses are t-statistics. Standard errors are clustered at the firm level. We report significance levels as follows:* * $p < 0.10$, $**\,p < 0.05$, $***p < 0.001$.

Table 11. Heterogeneity From Different Ownership

	Sub-groups		All sample
	(1) Non-SOEs	(2) SOEs	(3) Non-SOEs and SOEs
$CPUdivstd$	0.454***	0.081**	
	(4.771)	(2.253)	
$CPUdivstd \times SOE = 0(Non-SOEs)$			0.512***
			(6.588)
$CPUdivstd \times SOE = 1(SOEs)$			0.050
			(1.285)
Adj R-squared	0.647	0.630	0.692
Obs.	1,840	3,119	4,959
Differences in coefficients across models (p-value)		0.010	
Linear combination test (p-value)			0.000

Note: *All regressions include control variables and fixed effects. The values in parentheses are t-statistics. Standard errors are clustered at the firm level. We report significance levels as follows:* * $p < 0.10$, $**p < 0.05$, $***p < 0.001$.

Table 12. Heterogeneity From Supply Chain Concentration

	Sub-groups		Sub-sample
	(1)	(2)	(3)
	SupplyChain = 0(LSP)	SupplyChain = 1(HSP)	LSP and HSP
$CPUdivstd$	0.420***	0.005	
	(4.577)	(0.102)	
$CPUdivstd \times SupplyChain = 0(LSP)$			0.200**
			(2.482)
$CPUdivstd \times SupplyChain = 1(HSP)$			0.047
			(0.979)
Adj R-squared	0.711	0.729	0.703
Obs.	1,138	1,543	2,624
Differences in coefficients across models (p-value)		0.044	
Linear combination test (p-value)			0.006

Note: *All regressions include control variables and fixed effects. The values in parentheses are t-statistics. Standard errors are clustered at the firm level. We report significance levels as follows:* * $p < 0.10$, $**p < 0.05$, $***p < 0.001$.

Table 13. Mechanism: *Spread* and *Zscore*, T-Test and Regression Results

(a) T-Test: <=1.81 and >=2.67

Variable	*Zscore* >= 2.67		*Zscore* <= 1.81		Mean1 - Mean2
	Obs.	Mean1	Obs.	Mean2	
Spread	1,526	1.940	3,433	2.148	-0.209***

(b) T-Test: <= $p25$ and >= $p75$

Variable	*Zscore* >= $p75$		*Zscore* <= $p25$		Mean1 - Mean2
	Obs.	Mean1	Obs.	Mean2	
Spread	1,257	1.951	1,234	2.491	-0.540***

(c) Regression Analysis of *Spread* on *Zscore*

	(1)	(2)	(3)
	Spread	Spread	Spread
CPUdivstd		0.100**	0.145**
		(2.305)	(3.298)
Zscore	-0.185***	-0.181***	
	(-4.611)	(-4.567)	
Controls	No	Yes	Yes
Fixed effects	Yes	Yes	Yes
Adj R-squared	0.692	0.692	0.683
Obs.	4,959	4,959	4,959

Note: *The values in parentheses are t-statistics. Standard errors are clustered at the firm level. We report significance levels as follows:* * $p < 0.10$, $**p < 0.05$, $***p < 0.001$.

Table 14. ESG Rating and ESG Disagreement

	ESGscore is measured by						
	(1) Bloomberg	(2) FTSE	(3) Wind	(4) SSI	(5) SynTao	(6) SusallWave	(7) ESG disagreement
$CPUdivstd$	0.278**	0.450**	0.622***	0.388**	0.261**	0.472***	0.104*
	(2.798)	(3.169)	(4.472)	(2.852)	(2.632)	(3.875)	(1.711)
$ESGscore$	-0.010**	-0.004	0.076	-0.078**	0.080**	0.044**	
	(-2.182)	(-0.023)	(1.437)	(-3.107)	(2.004)	(2.299)	
$CPUdivstd \times ESGscore$	-0.005*	-0.099*	-0.061**	-0.053*	-0.021	-0.019**	
	(-1.688)	(-1.926)	(-2.687)	(-1.858)	(-0.910)	(-2.324)	
$ESGgap$							-0.034
							(-0.199)
$CPUdivstd \times ESGgap$							0.313**
							(1.990)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.667	0.745	0.762	0.682	0.706	0.748	0.676
Obs.	3,825	1,297	2,180	4,839	2,330	1,666	4,231

Note: *In this table, FTSE and Bloomberg refer to FTSE Russell's ESG Scores and Bloomberg ESG, respectively. SSI, FIN, SynTao, and Wind are ESG scores construed by Chinese agencies, whose Chinese pinyin is Huázhèng, Ménglàng, Shngdào Róngl and Wàndé , receptively.The values in parentheses are t-statistics. Standard errors are clustered at the firm level. We report significance levels as follows:* * $p < 0.10$, $**p < 0.05$, $***p < 0.001$.

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Appendix

A GPT Prompt

prompt = "role": "user", "content": """

The following text is an excerpt from the Corporate Social Responsibility (CSR) report of a publicly listed company in China. It reports the company's CSR practices for the year.

You are an analyst specializing in the intersection of environmental risk, climate change, and economics.

Task Requirements:

Based on the provided text and your professional judgment, summarize and assess the company's potential climate policy uncertainty (CPU) risks.

Specific Requirements:

Information Extraction: Identify information related to climate policy uncertainty from the text, including but not limited to environmental regulations, carbon emission limits, or environmental policy changes that may be introduced or adjusted by the government or regulatory bodies, and the uncertain impact they may have on the companys business, compliance, and strategy.

Risk Assessment: Briefly analyze the potential risks that these uncertainties could pose to the company.

Answer Guidelines:

Avoid Repetition: Do not repeat the input text in your response.

Third-Person Writing: Your response must be written in the third person (with the company as the subject).

Answer Format: Please respond in paragraph form.

When Unable to Judge: If you are unable to make a judgment, your response should simply be "NA."

No Need for Explanation: You do not need to explain why you are unable to make an assessment. Simply provide "NA" when applicable.

Professional Inference: You may base your analysis and inference on the provided text and your expertise, but ensure that all inferences are well-founded and closely related to the input text.

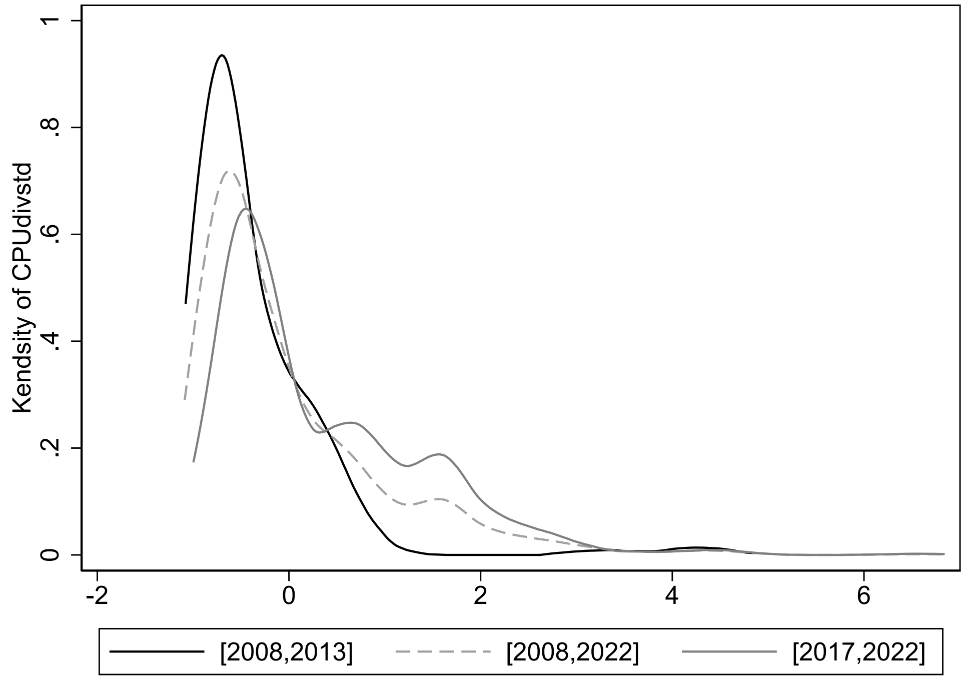
Clarity and Structure: Present the results clearly and in an organized manner for ease of subsequent analysis.

Important Reminder: Please strictly adhere to the above requirements in your response.

"""

B Reliability of $CPUdivstd$

Figure B.1. Kernel Density Probability Curves of $CPUdivstd$ for Different Time Periods



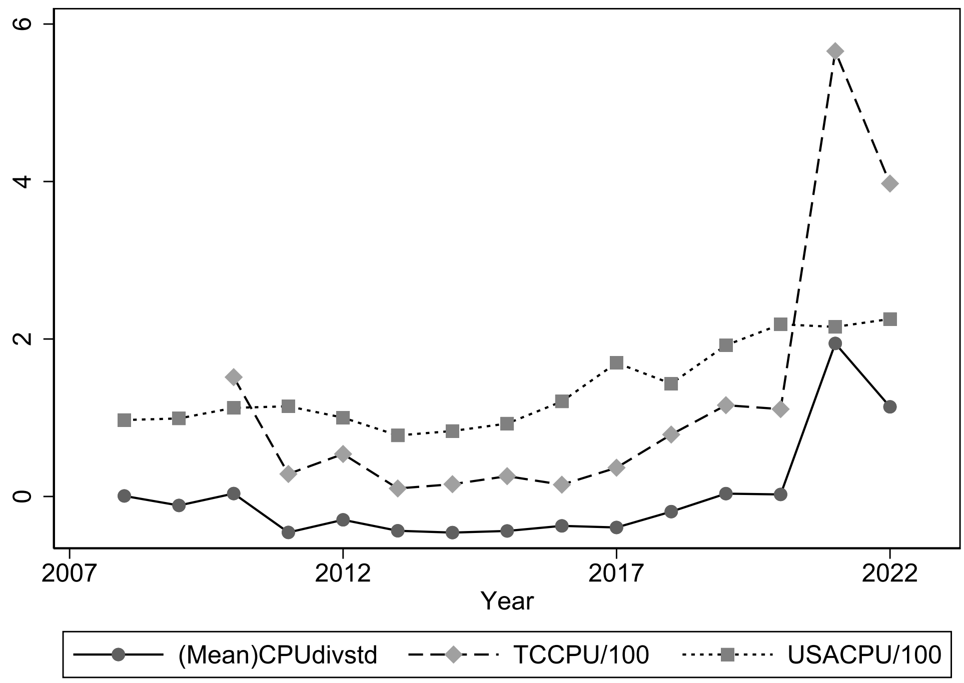
Note: *This figure displays the kernel density probability curves of $CPUdivstd$ across different time intervals. The black curve represents $CPUdivstd$ for the 2008-2013 sample, while the gray curve corresponds to the 2017-2022 period. The dashed line illustrates the $CPUdivstd$ for the entire sample period from 2008 to 2022. From this figure, we can observe at least three key points: (1) There is significant dispersion in firms' CPU, as indicated by the right-skewed tail. This suggests that some firms are facing substantial risks from CPU; (2) The heavy-tail effect becomes more pronounced over time, particularly in the later period. This suggests that, as extreme climate events become more frequent and relevant policies are increasingly implemented, firms are exposed to greater risks from climate policy uncertainty; (3) The overall rightward shift in the probability density curves reflects an increasing trend in climate uncertainty risks over time. This aligns with findings from other scholars (Gavriilidis, 2021; Lee and Cho, 2023), who have observed that the market's CPU risks are becoming more severe.*

Table B.1. Pearson Correlation Coefficient Test

Note: *This table presents the Pearson correlation coefficients between various variables, focusing on the relationship between the firm-level CPU measure and macro-level CPU indices. Firstly, we observe that the firm-level CPU measure ($CPUdivstd$) exhibits a strong correlation with the $TCCPU$ index, with a correlation coefficient more than* 0.7*, significant at the 1% level. This indicates a robust linear relationship between our firm-level CPU measure and the Twitter-based Chinese Climate Policy Uncertainty (TCCPU) index, lending further support to the validity and credibility of the CPU metric constructed in this study. Moreover, the correlation between $CPUdivstd$ and the $USACPU$ index, while lower than the correlation between $TCCPU$ and $USACPU$, is still statistically significant. This suggests that firm-level CPU is also influenced by uncertainty in the global market, but is more sensitive to domestic climate policy fluctuations, which aligns with expectations. The $CPUdivstd$ is calculated according to the methodology outlined in Section 3. The $TCCPU$ index is obtained from Lee and Cho (2023), while the USACPU index is sourced from Gavriilidis (2021). By comparing these different levels of CPU indicators, we gain a more comprehensive understanding of firms' responses to CPU, further demonstrating the robustness of our firm-level CPU measure. We report significance levels as follows: ** $p < 0.10$, $**p < 0.05$, $***p < 0.001$.

	$CPUdivstd$	$TCCPU$	$USACPU$
$CPUdivstd$	1.000		
$TCCPU$	0.707***	1.000	
$USACPU$	0.494***	0.685***	1.000

Figure B.2. Trends in Different CPU Measurements



Note: *This figure illustrates the trends of various CPU measurement methods over time. We calculate the annual mean values of $CPUdivstd$, and to make the comparison more intuitive, we scaled the $TCCPU$ and $USACPU$ indices by dividing them by 100. The figure reveals that all three CPU measures follow a similar trend over time. Notably, the $CPUdivstd$ and TCCPU indices show strong alignment, where the key spikes in uncertainty occur at the same points. This consistency in trends, particularly between $CPUdivstd$ and $TCCPU$, highlights the reliability of our firm-level CPU measurement. The fact that the major fluctuation points coincide across different measures further strengthens the validity of the CPU measurement.*

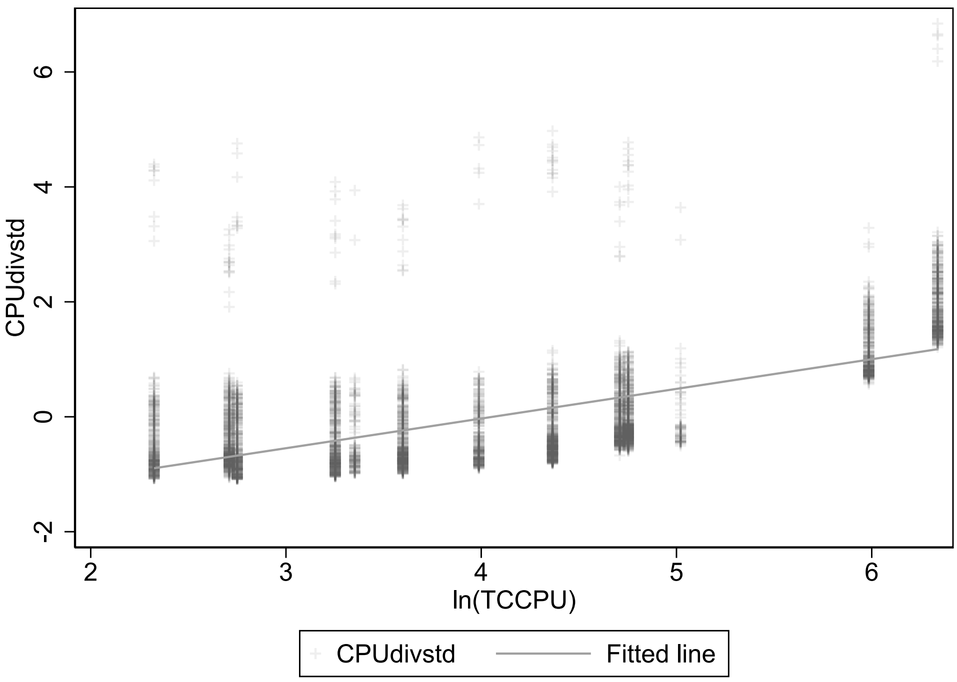


Figure B.3. Relationship Between $CPUdivstd$ and TCCPU

Note: *This figure illustrates the relationship between $CPUdivstd$ and $TCCPU$. The cross points on the graph represent the individual values of $CPUdivstd$, while the x-axis indicates the logarithmic values of $TCCPU$. The solid line represents the fitted trend line. From the figure, we can observe that the two variables exhibit a similar pattern. When $TCCPU$ is relatively low, firms generally experience lower levels of CPU on average. However, even in these conditions, some firms still face significant CPU, as indicated by the higher values of $CPUdivstd$. Our regression of $ln(TCCPU)$ on $CPUdivstd$ further supports this visual relationship, showing that $CPUdivstd$ explains approximately 50% of the variance in $ln(TCCPU)$. This indicates a substantial connection between the two variables and highlights the explanatory power of $CPUdivstd$ in capturing fluctuations in CPU.*

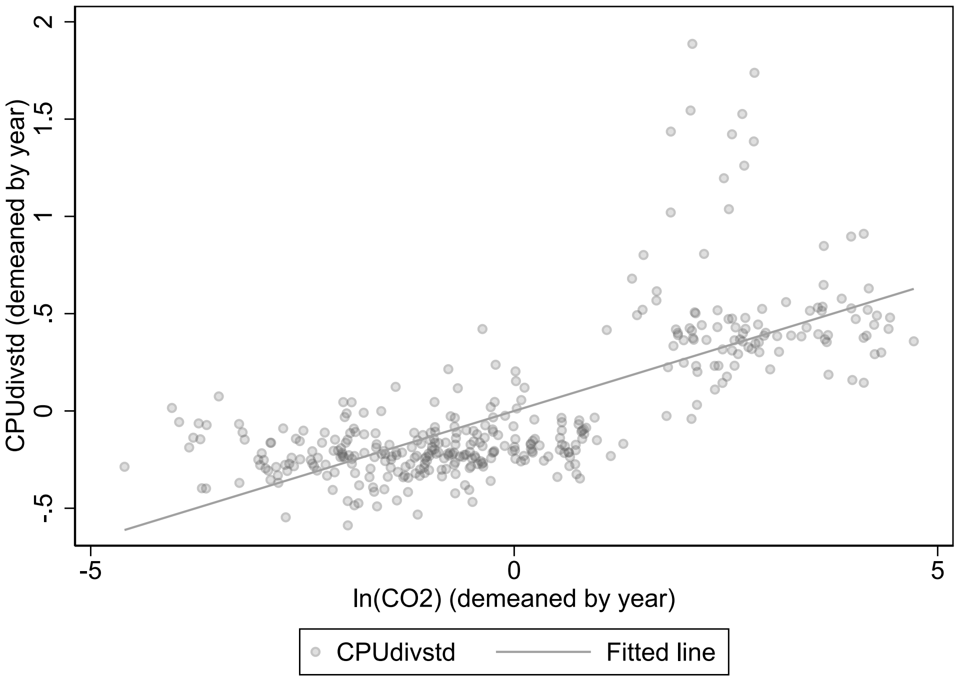


Figure B.4. Relationship Between *CPUdivstd* and Industry CO_2 Emissions

Note: *This figure illustrates the relationship between CPUdivstd and industry-level CO_2 emissions (measured in 10,000 tons). Since both variables are panel data, we applied a within-group de-meaning transformation. Specifically, the x-axis represents the logged de-meaned CO_2 emissions, with CO_2 data sourced from the China Emission Accounts and Datasets (CEADs). This data ranges from 2008 to 2022. The y-axis represents CPUdivstd, where we first aggregated CPUdivstd averages by year and industry (for manufacturing sectors, we used subcategories such as C26 and C31; for other sectors, we used broader categories like A or B). The results reveal a positive correlation between CPUdivstd and CO_2 emissions. A subsequent regression analysis shows that CO_2 emissions explain approximately 51% of the variation in CPUdivstd, aligning with findings from the existing literature. Specifically, firms with higher CO_2 emissions are more exposed to CPU, as most current policies target carbon emissions (Stern, 2008; Ilhan et al., 2021). On the other hand, even in low-carbon sectors with relatively lower CO_2 emissions, we observe that some firms still face some CPU. This observation aligns with Noailly et al. (2022), who noted that CPU not only affects high-emission firms but also impedes investment in clean technologies and the low-carbon economy. By comparing CPU with industry-level CO_2 emissions, this figure further demonstrates the reliability of the CPUdivstd measure used in this study.*

C Include Market Control Variables Instead

Table C.1. Regressions With Market Control Variables

Note: *This table does not include year-fixed effects but instead incorporates market control variables: the Economic Policy Uncertainty (EPU) Index, the natural logarithm of GDP (in billions of RMB), and the M2 money supply growth rate (in percentage terms). The EPU data is sourced from* `https://www.policyuncertainty.com/china_epu.html` *based on the method of Baker et al. (2016) and Davis et al. (2019). We calculate the annual average of the EPU and divide it by 100. GDP and M2 data are obtained from the National Bureau of Statistics. Our results show that the estimated coefficient for EPU is significantly positive, while the coefficients for GDP and M2 are negative, which aligns with expectations. Furthermore, after controlling for these market variables, the coefficient for $CPUdivstd$ remains significantly positive, also in line with our expectations. Additionally, we observe that, compared to the baseline results in Table 3, the adjusted R-squared in this table is slightly lower, and there is a potential risk of overestimating the effect of $CPUdivstd$. Therefore, we consider it more appropriate to include year-fixed effects in the baseline regression for greater accuracy. The values in parentheses are t-statistics. Standard errors are clustered at the firm level. We report significance levels as follows:* $*\ p < 0.10$, $**\ p < 0.05$, $***p < 0.001$.

	(1) Spread	(2) Spread
$CPUdivstd$	0.185***	0.208***
	(5.937)	(6.878)
EPU	0.083***	0.094***
	(5.922)	(6.660)
GDP	-1.360***	-0.597*
	(-8.021)	(-1.700)
$M2$	-0.047***	-0.044***
	(-4.829)	(-4.267)
Constant	20.758***	16.603***
	(8.890)	(4.669)
Controls	No	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	No	No
Adj R-squared	0.620	0.636
Obs.	4,959	4,959

D SSIV

The *SSIV* is constructed as:

$$SSIV_{pt} = \sum_{s=1}^{S} Share_{ps,t=2007} \cdot Shift_{st} \tag{D.1}$$

where the *Shift* component is obtained as:

$$Shift_{st} = \frac{1}{N_s} \sum CPUdivstd_{jst} \tag{D.2}$$

N_s is the total number of firms in industry s, and $CPUdivstd_{jst}$ is CPU for firm j in industry s in year t. The *Share* component is:

$$Share_{ps,t=2007} = \frac{CO_2\text{Emissions}_{ps,t=2007}}{\sum_{S}^{S=1} CO_2\text{Emissions}_{ps,t=2007}} \tag{D.3}$$

where $CO_2\text{Emissions}_{ps,t=2007}$ is the CO_2 emissions for industry s in province p in the year 2007, and J is the total number of industries in the sample.

E Altman Z-score

The Altman Z-Score model is a financial metric used to predict the likelihood of a company's bankruptcy. This model combines several financial ratios to assess the company's overall financial health. According to the document of CSMAR, the Z-Score formula is:

$$Z = 1.2 \times X_1 + 1.4 \times X_2 + 3.3 \times X_3 + 0.6 \times X_4 + 0.999 \times X_5 \tag{E.4}$$

where X_1 represents the Working Capital to Total Assets ratio, which measures the companys short-term liquidity. X_2 is the Retained Earnings to Total Assets ratio, indicating the companys profitability and financial stability over time. X_3 represents the Earnings Before Interest and Taxes (EBIT) to Total Assets ratio, evaluating the companys operating efficiency and profitability. X_4 is the Market Value of Equity to Total Liabilities ratio, which assesses the companys capital structure and ability to cover its liabilities. X_5 is the Sales to Total Assets ratio, reflecting the efficiency of the companys asset utilization in generating sales.

F More Robustness Checks

Table F.1. More Robust Checks

Note: *This table presents robustness by adding more fixed effects (Table F.1a), narrowing samples (column 1 of Table F.1b) and using different clustering ways (columns 2 and 3 of Table F.1b). In column 1 of Table F.1b, observations after 2019 are not included to exclude the effect of COVID-19. Standard errors are clustered at industry and province levels, respectively in columns 2 and 3 of Table F.1b. For Table F.1a and column 1 of Table F.1b, standard errors are clustered at the firm level. The values in parentheses are t-statistics. We report significance levels as follows:* $* \, p < 0.10$, $** \, p < 0.05$, $*** p < 0.001$.

(a) Adding More Fixed Effects

	(1) Spread	(2) Spread	(3) Spread
$CPUdivstd$	0.136**	0.134**	0.148**
	(3.045)	(3.114)	(3.204)
Controls	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Year-Province fixed effects	Yes	No	Yes
Year-Industry fixed effects	No	Yes	Yes
Adj R-squared	0.703	0.706	0.723
Obs.	4,919	4,852	4,820

(b) Narrow Sample and Standard Errors Clustering at Different Levels

	$Year <= 2019$	Clustering	
	(1) Sub-sample	(2) At industry level	(3) At province level
$CPUdivstd$	0.103**	0.145*	0.145***
	(2.444)	(1.820)	(4.701)
Controls	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Adj R-squared	0.684	0.683	0.683
Obs.	3,739	4,959	4,959

G CPU on credit rating and bond issuance amount

Table G.1. Impacts on Credit Rating and Bond Issuance Amount

Note: *This table documents regression results of CPU's impact on credit rating (column 1) and bond issuance amount (column 2). In column 1, we propose the following regression model:*

$$RateAve_{jt} = \alpha + \beta_1 CPUdivstd_{jt} + \beta_1 IssuerControls1_{j,t-1} + \lambda_t + \lambda_j + \varepsilon_{jt} \tag{G.5}$$

where $RateAve_{jt}$ is the average rating of bonds issued by firm j in year t. And we find that the coefficient of $CPUdivstd$ is significant at the 5% level, indicating that rating agencies consider climate policy uncertainty when assessing firms' creditworthiness. However, an increase of one standard deviation in $CPUdivstd$ only reduces the linearized rating value by approximately 0.04 ($-0.041 \times 0.962 = -0.04$), which accounts for only 1% of the $RATE$ average ($0.04/4.159 = 0.01$). In column 2, we propose the following regression:

$$Amount_{jt} = \alpha + \beta_1 CPUdivstd_{jt} + \beta_2 IssuerControls_{j,t-1} + \lambda_t + \lambda_j + \varepsilon_{jt} \tag{G.6}$$

*where Amount represents the total bonds (unit: CNY 100M) issued by firm j in year t, expressed in logarithmic form. The coefficient of $CPUdivstd$ is not significant, suggesting that CPU has no substantial impact on firms' bond financing behavior. The values in parentheses are t-statistics. Standard errors are clustered at the firm level. We report significance levels as follows: * $p < 0.10$, $**\, p < 0.05$, $***p < 0.001$.*

	(1)	(2)
	RateAve	Amount
$CPUdivstd$	-0.041**	0.035
	(-2.279)	(1.000)
Controls	Yes	Yes
Fixed effects	Yes	Yes
Adj R-squared	0.883	0.899
Obs.	4,959	4,959