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Article

Does climate policy uncertainty influence the corporate cost of debt?

Pengju Zheng, Jun Cui, Bona Xiao*

Solbridge International School of Business, Woosong University, Daejeon 34613, Korea
*** Corresponding author:** Bona Xiao, bona.xiao222@student.solbridge.ac.kr

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Abstract: This paper employs a sample of Chinese A-share listed companies spanning from 2011 to 2022 to empirically investigate the influence of climate policy uncertainty on the corporate cost of debt, based on the theory of financial friction. We find that climate policy uncertainty significantly increases the corporate cost of debt, and the result is supported by robustness tests. To avoid biases arisen from endogeneity, this paper introduces an instrumental variable approach and propensity score matching method for verification. The endogeneity test results support the baseline regression results as well. Finally, this paper also discovers that financing constraints are the potential mechanism behind the impact of climate policy uncertainty on the corporate cost of debt.

Keywords: climate policy uncertainty; cost of debt; financial friction; financial constraints

1. Introduction

In recent decades, with the frequent occurrence of various global meteorological disasters, climate change and environmental sustainability have become the most pressing issues that society must face to develop (Iqbal et al., 2024).

To respond effectively to the challenges of climate change and to promote sustainable development, governments have introduced several policies. However, the frequent adjustments of these climate policies have raised the issue of policy uncertainty, which constitutes a significant risk factor for businesses, investors, and lending institutions. Specifically, policy uncertainty tends to motivate these market players to adopt a more conservative strategy (Sendstad and Chronopoulos, 2020). This may limit their innovative dynamism and pace of expansion, which in turn affects the overall operational efficiency and market competitiveness of the firm.

Gavriilidis (2021) is the first person who introduced a new method for measuring U.S. climate policy uncertainty based on news from major U.S. newspapers. In 2023, Ma et al. (2023) proposed a Chinese climate policy uncertainty index which could be more relevant to the characteristics of the Chinese market. Prior studies have found that climate policy uncertainty has several economic impacts on firms, and these impacts are normally negative according to these two indexes. Climate policy uncertainty can significantly inhibit firms' total factor productivity, and the total factor productivity of non-state-owned firms is more susceptible to climate policy uncertainty (Ren et al., 2022). Climate policy uncertainty can have a negative impact on sovereign bond returns and reduce the earnings of the business (Jia et al., 2024). Ren et al. (2024) find that the increase in climate policy uncertainty has a dampening effect on corporate financialization, and this relationship is more pronounced in the energy sector by using a fixed effects model.

However, few studies have summarized the impact of climate policy uncertainty on corporate debt, in particular, the corporate cost of debt. Therefore, we will analyze the impact of climate policy uncertainty on firms from the perspective of the cost of corporate debt.

Debt financing is one of the most important channels through which enterprises can obtain capital. For firms, the scale and cost of debt financing often have a direct impact on their development (Graham et al., 2008). Creditors will be more likely to assess the cost of a firm's debt in terms of its business conditions and risks. According to the theory of financial market friction, when the market is faced with potential risks brought about by uncertainty, the impact on the financing of the enterprise tends to be negative, resulting in financial difficulties for the enterprise.

As to the issue of whether uncertain environmental factors can influence the corporate cost of debt, the existing literature finds that firms with higher carbon risk face greater costs of debt (Owalabi et al., 2024). Shi et al. (2024) have found that a significant negative correlation does exist between ESG performance and the cost of debt. Better ESG performance reduces the corporate cost of debt. Using a sample of 163,243 firm-years from 17 countries, Tran (2021) finds that economic policy uncertainty positively affects the cost of debt, and this effect is stronger during the global financial crisis from 2008 to 2009. That means that uncertainty increases the corporate cost of debt. Overall, the uncertainty and negative ESG performance will increase the cost of debt.

According to the theory of financial frictions, frictions in financial markets lead to volatility in macroeconomic outcomes (Arellano et al., 2012). And it is this climate policy uncertainty that triggers this volatility. Gilchrist et al. (2014) point out that firms generally face multiple challenges, including uncertainty, investment irreversibility, fixed investment costs, and frictions in debt and equity markets, and these financial frictions continue to exacerbate the financial constraints of firms. As financing sources narrow and become more restrictive, firms are forced to turn to new and more expensive sources of financing to obtain funds (Hachem, 2018). This process further pushes up the cost of debt financing for firms. Based on the above analysis, we propose the following hypotheses:

H1: Based on the financial friction theory, climate policy uncertainty leads to an increase in the corporate cost of debt.

This paper focuses on climate policy uncertainties in China. Firstly, in response to increasing climate risks, China has enacted numerous emission reduction measures and has announced a goal of carbon neutrality by 2050 (Li et al., 2024). Furthermore, Chinese companies rely heavily on short-term loans as a means of financing (Fan et al., 2012). Short-term loans are often associated with a higher cost of capital. In this context, using Chinese-listed companies as the sample for empirical research will provide a more comprehensive setting for this study.

Utilizing the annual data of Chinese A-share listed firms from 2011 to 2022 and the index of Chinese climate policy uncertainty for empirical analysis, our findings are summarized as follows:

Firstly, the results show that climate policy uncertainty significantly enhances firms' cost of debt, and the results still hold up to pass the robustness and endogeneity tests.

Secondly, the relationship is more significant among non-state-owned enterprises, firms in the eastern region with higher carbon emissions and firms with more severe agency problems. Finally, we also find that climate policy uncertainty significantly increases firms' financing constraints, which in turn forces firms to passively receive higher costs of debt.

This paper contributes to prior research in the following ways: Firstly, lots of the existing studies on climate policy uncertainty utilize the U.S. climate policy uncertainty index to study the data of Chinese firms, for example Dai and Zhang (2023); Ren et al. (2022), use the U.S. climate policy uncertainty index to match China's firm-level total factor productivity and risks taken by the bank. In this paper, we use the Chinese climate policy uncertainty index, which is more in line with Chinese characteristics, so as to be more objective.

Secondly, this paper finds for the first time that a significant positive relationship exists between climate policy uncertainty and cost of debt for Chinese listed firms, which provides a reference for corporate decision makers to make corresponding financing decisions and business strategies.

Thirdly, this study contributes to enriching the emerging research on the effects of climate policy uncertainty, such as political rights (Qi et al., 2010), board diversity (Aksoy and Yilmaz, 2023), environment regulation (Ni et al., 2022), acquisitions (Wang et al., 2021); ESG practice (Eliwa et al., 2021).

Finally, this paper contributes to the understanding of the heterogeneity effect between climate policy uncertainty and cost of debt, showing that this positive correlation is more pronounced in non-SOEs, firms in the eastern region and firms with severe agency problems. And we also explore potential mechanisms by which climate policy uncertainty can affect the cost of debt, such as financial constraints.

This paper is organized as follows: In Section 2, we present the paper's use of the sample and methodology used in this paper; and Section 3 presents the empirical results, including tests of the baseline model, robustness tests, heterogeneity analysis, and endogeneity tests; Section 4 focuses on the descriptive tests of heterogeneity; Section 5 shows the description and tests of potential mechanisms; Section 6 presents conclusions, future recommendations and implications.

2. Methodology

2.1. Sample data sources

Utilizing the data from Chinese listed non-financial firms from 2011 to 2022 as our empirical sample, some observations were excluded according to the following criteria. Firstly, ST, *ST, and PT listed firms. Secondly, samples with missing data. In order to mitigate the influence of extreme values, we shrink the continuous variables at the upper and lower 1% levels. Finally, we obtained 20,426 annual observations. All the data at the firm level were obtained from the CSMAR[1], and the annual Chinese climate policy uncertainty index is from the following websites:

https://figshare.com/articles/dataset/China_s_CPU_index/24071193/1?file=42231762

2.2. Measurements of variables

This paper introduces corporate cost of debt as the dependent variable. Referring to Li, Padmanabhan, et al. (2024) and Wang et al. (2019), we employ the financial expense divided by total debt to measure the cost of debt (Cod). We formulate the following model to estimate the cost of debt (As shown in Equation (1)).

$$Cod_{i,t} = Financial\ Expense_{i,t}/Total\ Debt_{i,t} \quad (1)$$

Equation (1). The model to estimate the cost of debt (Source: Author's own work). where *i* indexes the firm and *t* is the year.

Next, in our baseline regression analysis, the independent variable is climate policy uncertainty. This uncertainty is quantified through an index that tallies the number of news articles pertaining to climate policy in prominent newspapers and on social media. Previous studies have frequently utilized statistics from indices such as the U.S. climate policy uncertainty indices for empirical analysis. Due to the sample of this paper coming from China's stock market, we chose the Chinese climate policy uncertainty index (Ccpu) referred to Ma et al. (2023) to measure the dependent variable.

We also control some firm characteristics variables in our baseline regression model. The following control variables are selected: firm age (Age), firm size (Size), property rights (Soe), financial leverage (Leverage), growth rate (Growth), operating cashflow (Cashflow), board size (Board), independent director (Independent), duality (Dual), largest shareholders (Top1), and Tobin's Q value (Tobinq).

2.3. Empirical framework

The measurements of all main variables are represented in **Table 1** above. We formulate the following model to further verify the impact of climate policy uncertainty on corporate cost of debt (As shown in Equation (2)).

$$Cod_{i,t} = \alpha_0 + \alpha_1 Ccpu_t + \alpha_2 Controls_{i,t} + \gamma_{industry} + \varepsilon_{city} + \theta \quad (2)$$

Equation (2). The impact of climate policy uncertainty on corporate cost of debt (Source: Author's own work). where *i* indexes the firm and *t* is the year. γ industry and εcity denote industry and fixed effects and clustered standard errors at the fixed level. No year-fixed effects are introduced because Ccpu is country-level data and there is no difference in Ccpu corresponding to all firms in the same given year.

Table 1. Measurements of main variables.

Variable	Symbol	Measurement
Cost of debt	Cod	Financial expense / total debt
Climate policy uncertainty index	Ccpu	Climate policy uncertainty index for China in a given year which download from the website reported earlier
Firm age	Age	Natural logarithm of listed years
Firm size	Size	Natural logarithm of total assets
Property rights	Soe	Equals 1 if the fiscal firm is state owned enterprise, equals 0 otherwise
Financial leverage	Leverage	Total liabilities / total assets

Table 1. (*Continued*).

Variable	Symbol	Measurement
Growth rate	Growth	Growth rate of operating revenue
Operating cashflow	Cashflow	Operating cashflow / total assets
Board size	Board	Natural logarithm of board member number
Independent director	Independent	The number of independent directors / total number of directors
Duality	Dual	Equals 1 if chief executive officer and chairman of the board are the same person, equals 0 otherwise
Largest shareholders	Top1	The proportion of shares owned by the largest shareholder
Tobin's Q value	TobinQ	Tobin's Q value of a given firm

Notes. (Source: Author's own work).

3. Empirical results and analysis

3.1. Descriptive statistics

Table 2 represents the descriptive statistics of the main variables and statistical results are retained to three decimal places. Obviously, the results show that there is a significant difference in the cost of debt financing among different firms. Overall, the standard deviation of the climate policy uncertainty index is 0.570, the minimum value is 0.559, and the maximum value is 3.120, indicating that firms face more pronounced climate policy changes. Our statistics are very close to those of Iqbal et al. (2024) on the climate policy uncertainty index, thus indicating that our data are reliable.

Table 2. Descriptive statistics of main variables.

Variable	Obs	Mean	Std. dev.	Min	Max
Cod	20,426	0.006	0.036	−0.170	0.060
Ccpu	20,426	1.832	0.570	0.559	3.120
Age	20,426	2.331	0.665	0.693	3.401
Size	20,426	22.390	1.330	20.026	26.511
Soe	20,426	0.374	0.484	0.000	1.000
Leverage	20,426	0.434	0.203	0.055	0.888
Growth	20,426	0.169	0.373	−0.505	2.204
Cashflow	20,426	0.047	0.065	−0.137	0.234
Board	20,426	2.132	0.198	1.609	2.708
Independent	20,426	0.376	0.054	0.333	0.571
Dual	20,426	0.272	0.445	0.000	1.000
Top1	20,426	0.335	0.150	0.080	0.743
TobinQ	20,426	2.008	1.273	0.847	8.264

Note: This table presents the descriptive statistics of the main variables used in this paper. We winsorise the main firm level variables at the 1% and 99% levels to mitigate the influence of extreme values. All statistical results are retained to three decimal places (Source: Author's own work).

3.2. Baseline regression results

In **Table 3**, it represents the regression results of our baseline model. We compared baseline regressions across conditions. It is clear that our baseline regression results are significantly negatively correlated, regardless of the conditions after the introduction of control variables of firm characteristics. Column (2) reports the regression coefficient of climate policy uncertainty on cost of debt is 0.003 and significantly at 1% level. This result investigates that there is a positive relationship between climate policy uncertainty and cost of debt, thereby providing evidence to support the financial friction theory. It also further reveals how fluctuations in the policy environment directly influence the cost of debt financing in the context of global climate change. The positive correlation suggests that as climate policy uncertainty increases, the cost of debt faced by firms rises accordingly, thereby providing strong evidence to understand and address the impacts of climate change on financial markets and the financial position of firms.

Table 3. Baseline model regression.

	(1)	**(2)**
VARIABLE	**Cod**	**Cod**
Ccpu	0.002***	0.003***
	(0.001)	(0.000)
Age		0.008***
		(0.001)
Size		−0.002***
		(0.000)
Soe		−0.004***
		(0.001)
Leverage		0.098***
		(0.003)
Growth		0.002***
		(0.001)
Cashflow		−0.001
		(0.004)
Board		−0.002
		(0.002)
Independent		−0.001
		(0.007)
Dual		−0.001
		(0.001)
Top1		−0.013***
		(0.003)
Tobinq		−0.000
		(0.000)

Table 3. (*Continued*).

	(1)	(2)
VARIABLE	**Cod**	**Cod**
Constant	0.003	0.001
	(0.007)	(0.012)
Observations	20,426	20,426
R-squared	0.127	0.377
Industry FE	Yes	Yes
City FE	Yes	Yes
Cluster	Firm	Firm

Note: **Table 3** reports the baseline regression results, where results of Column (1) do not control year and city fixed effects; standard errors are not clustered at the firm level. Column (2) controls year and city fixed effects, with standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses (Source: Author's own work).

3.3. Robust tests

In this section, we will introduce additional tests to check the robustness of the main results presented earlier. These additional tests include an alternative cost of debt, sample adjustments, alternate model, instrumental variable approach, and propensity score matching method. The results are reported in following table.

3.3.1. An alternative cost of debt

In this paper, we initially use the ratio of financial expense to total debt as the core metric in assessing the cost of debt financing. Subsequently, we draw on the recent findings of Magnanelli and Izzo (2017) and Li, Hu, et al. (2024) and adopt an alternative measure, i.e., replacing the original dependent variable in the model with the ratio of interest expense to total debt. This adjustment aims to enhance the robustness of the results of the baseline regression analysis by introducing a different measure of finance costs, further validating and consolidating our analytical results (As shown in Equation (3)).

$$Cod\ alternate_{i,t} = Interest\ Expense_{i,t}/Total\ debt_{i,t} \tag{3}$$

Equation (3). different measure of finance costs (Source: Author's own work).
where i indexes the firm and t is the year.

Column (1) of **Table 4** represents the relationship between climate policy uncertainty and the alternate cost of debt. Clearly, there is a significant positive relationship between them, which can support our baseline regression results.

Table 4. Robust tests regressions.

	(1)	(2)	(3)
		(Before 2020)	(Tobit model)
VARIABLE	**Cod alternate**	**Cod**	**Cod**
Ccpu	0.001**	0.004***	0.003***
	(0.000)	(0.001)	(0.000)

Table 4. (*Continued*).

	(1)	(2)	(3)
		(Before 2020)	(Tobit model)
VARIABLE	Cod alternate	Cod	Cod
Age	0.001***	0.011***	0.008***
	(0.000)	(0.001)	(0.001)
Size	−0.001***	−0.001***	−0.002***
	(0.000)	(0.000)	(0.000)
Soe	−0.002***	−0.005***	−0.004***
	(0.001)	(0.001)	(0.001)
Leverage	0.028***	0.101***	0.098***
	(0.001)	(0.003)	(0.003)
Growth	−0.003***	0.003***	0.002***
	(0.000)	(0.001)	(0.001)
Cashflow	−0.002	−0.003	−0.001
	(0.002)	(0.005)	(0.004)
Board	0.001	−0.002	−0.002
	(0.001)	(0.003)	(0.002)
Independent	0.006	−0.004	−0.001
	(0.004)	(0.009)	(0.007)
Dual	−0.000	−0.001	−0.001
	(0.000)	(0.001)	(0.001)
Top1	−0.007***	−0.012***	−0.013***
	(0.001)	(0.003)	(0.003)
Tobinq	−0.001***	−0.001	−0.000
	(0.000)	(0.000)	(0.000)
Constant	0.041***	−0.017	0.001
	(0.006)	(0.014)	(0.011)
Observations	20,426	14,812	20,426
R-squared	0.331	0.411	
Industry FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Cluster	Firm	Firm	Firm

Note: In this table, Column (1) reports the regression relationship between climate policy uncertainty and the alternate variable of debt cost. Column (2) represents the relationship before 2020 due to avoid the effects of the global pandemic. Column (3) reports the regression results after adjusting the model. All the robust tests support our baseline regression result. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses (Source: Author's own work).

3.3.2. Sample adjustments

The ravages of the global pandemic and the subsequent socio-economic upheavals triggered have invariably exacerbated the financial pressures faced by firms. Against this backdrop, companies generally experienced tight financial flows, forcing them to seek additional sources of financing to sustain their operations. According to

Gopalakrishnan et al. (2022), debt financing activities of firms increased significantly during the influenza pandemic, becoming one of the most important means for many firms to alleviate financial pressures and ensure survival and growth. Therefore, in order to avoid any bias on our study due to the global impact on corporate debt financing, we exclude the samples in 2020 and after from the robustness test and re-run the regression analysis to ensure the robustness of the regression model.

Table 4 Column (2) represents the regression results by using a sample before 2020. It can be seen that, after excluding the effects of the epidemic, there is still a positive relationship between climate policy uncertainty and cost of debt, as well as being significantly at the 1% level. This result again proves the robustness of our regression model.

3.3.3. Alternate model (tobit model)

To avoid situations where the dependent variable is restricted or truncated, in this section, we use the Tobit model to verify the robustness of our baseline regression model. All variables and fixed effects are the same as in the baseline regression model; the standard errors are clustered at the firm level as well.

Table 4 Column (3) reports the regression results for using the Tobit model. The results are useful in proving that the relationship between climate policy uncertainty and the cost of debt is still significant and positive. In another word, by using the Tobit model, it shows that climate policy uncertainty may increase the cost of debt. This may reiterate our baseline results.

3.3.4. Instrumental variable approach

The endogeneity problem refers to the correlation between the dependent variables and the error term in the model, which may be due to omitted variables, measurement error, or simultaneity bias. Meanwhile, in order to test whether there is reverse causality between independent and dependent variables, we will introduce the instrumental variable test method to baseline the robustness of the model in this section.

Following the way of Zhang et al. (2024), we employ a one-year lag of climate policy uncertainty to be the instrumental variable. Because the previous climate policy uncertainty for the following year is relevant. But there is generally no correlation to the cost of debt in the following years. We introduced the instrumental variable Iv-*Ccpu* (one year lag of climate policy uncertainty) as a dependent variable into the baseline regression model and estimated their relationship again.

Table 5. Instrumental variable approach and propensity score matching method.

	(1)	(2)	(3)
	IV-1st stage	IV-2nd stage	Propensity score matching
VARIABLE	Ccpu	Cod	Cod
Ccpu		0.010***	0.002***
		(0.003)	(0.001)
Iv-Ccpu	0.161***		
	(0.009)		

Table 5. (*Continued*).

	(1)	**(2)**	**(3)**
	IV-1st stage	**IV-2nd stage**	**Propensity score matching**
VARIABLE	**Ccpu**	**Cod**	**Cod**
Age	−0.010*	0.006***	0.008***
	(0.006)	(0.001)	(0.001)
Size	0.011***	−0.002***	−0.003***
	(0.003)	(0.000)	(0.000)
Soe	−0.004	−0.004***	−0.004***
	(0.007)	(0.001)	(0.001)
Leverage	−0.018	0.093***	0.100***
	(0.019)	(0.003)	(0.004)
Growth	0.068***	0.001	0.002**
	(0.009)	(0.001)	(0.001)
Cashflow	−0.159***	0.001	0.004
	(0.052)	(0.005)	(0.007)
Board	0.016	−0.002	−0.003
	(0.018)	(0.002)	(0.003)
Independent	0.062	−0.000	−0.006
	(0.066)	(0.007)	(0.010)
Dual	−0.002	−0.001	−0.000
	(0.007)	(0.001)	(0.001)
Top1	−0.004	−0.014***	−0.011***
	(0.019)	(0.003)	(0.004)
Tobinq	0.013***	−0.001***	−0.000
	(0.003)	(0.000)	(0.000)
Constant	1.918***	0.002	0.027
	(0.081)	(0.015)	(0.017)
Observations	16,735	16,735	7,066
R-squared		0.354	0.388
Industry FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Cluster	Firm	Firm	Firm
Cragg-Donald Wald F statistic	430.75***		
Kleibergen-Paap Wald rk F statistic	332.39***		

Note: The results of the instrumental variable approach are reported in this table. Column (1) is the first stage of the instrumental variable approach, where the regression of the instrumental variable on the dependent variable results in a significant positive correlation. Column (2) reports the results of the second stage of the instrumental variable method. It shows that there is a significant positive relationship between climate policy uncertainty and the cost of debt by excluding reverse causality. Additionally, the instrumental variable approach passes the weak identification tests. Column (3) reports the results of the propensity score matching method, which also supports our baseline regression results by mitigating the sample selection bias. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses (Source: Author's own work).

Table 5 Clomun (1) and (2) show the regression results of our instrumental variables approach. In the first stage, there is a significant positive correlation between instrumental and independent variables. It indicates that the climate policy uncertainty in the previous year may have a positive association with the one in the next year in China. And in the second stage, there is still a significant positive association between the independent variable climate policy uncertainty and the dependent variable (cost of debt) by excluding reverse causality, which again supports the robustness of our baseline regression. Meanwhile, our test results pass the weak-instrument-robust inference; the Cragg-Donald Wald F statistic and Kleibergen-Paap Wald rk F statistic are both significantly at the 1% level.

3.3.5. Propensity score matching method

In order to effectively mitigate the endogeneity problem caused by sample selection bias, this section of the study adopts the propensity score matching method as a strategy. Specifically, we divided the sample into experimental and control groups based on the median climate policy uncertainty as the division criterion. In the first stage, we apply a logit regression model to accurately estimate the propensity score for each observation, which reflects the conditional probability that the observation is assigned to the experimental group rather than the control group. Subsequently, in the second stage, we use these propensity scores to perform nearest-neighbor matching to ensure that the experimental group achieves maximum similarity with the control group on all control variables covered by the baseline model. Through this process, we aim to construct a more balanced sample set to more accurately assess treatment effects.

The results presented in Column (3) of **Table 5** not only revalidate the main findings of the baseline model but also further strengthen the support for the financial frictions theory. This result suggests that the original findings remain robust and valid even after eliminating potential sample selection bias through propensity score matching.

4. Heterogeneity test

In exploring potential influence relationships, we introduce several key variables to identify as important factors that may trigger heterogeneous effects, which can significantly alter the original framework of correlation analysis. Next, we elaborate on the reason why we chose to include these variables in our study and reveal empirical results that are directly relevant to the exploration of heterogeneous effects.

4.1. Property rights

First, state owned enterprises can make it easier for firms to obtain lower-cost long-term debt from banks (Li et al., 2009). This is because long-term debt typically has lower financing costs compared to short-term debt. Second, in the face of financial distress or market volatility, state-owned shareholders take a variety of specific actions to support these firms (Cong et al., 2019), which include, but are not limited to, debt relief, direct financial assistance programs, and preferential access to capital. In addition, SOEs are subject to stricter regulation, thus reducing the likelihood that they will rely on high-cost short-term debt (Li, Huang, et al., 2024). Thus, we predict that the increase in financing costs for non-SOEs will be stronger than for SOEs in the face of the risks posed by climate policy uncertainty. Dividing the sample into SOES and non-SOEs for separate regression analyses. The results obtained are shown in **Table 6** columns (1) and (2).

Table 6. Heterogeneity test.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLE	**Cod**	**Cod**	**Cod**	**Cod**	**Cod**	**Cod**
	SOEs	**Non-SOEs**	**Eastern**	**Non-eastern**	**Highagency aafeacenga gency agency agency**	**Lowagency**
Ccpu	0.001	0.004***	0.003***	0.001	0.005***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.002*	0.011***	0.009***	0.008***	0.012***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Size	−0.002***	−0.002***	−0.002***	−0.002***	0.000	−0.002***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Soe			−0.004***	−0.003	−0.004***	−0.003***
			(0.001)	(0.002)	(0.001)	(0.001)
Leverage	0.068***	0.116***	0.104***	0.082***	0.116***	0.073***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Growth	−0.001*	0.003***	0.001*	0.002**	0.004***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Cashflow	0.009	−0.007	0.004	−0.013*	−0.009	0.005
	(0.005)	(0.006)	(0.005)	(0.008)	(0.008)	(0.004)
Board	−0.000	−0.003	−0.002	−0.000	−0.004	−0.000
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.002)
Independent	−0.000	0.001	−0.004	0.010	0.003	0.005
	(0.008)	(0.011)	(0.009)	(0.011)	(0.012)	(0.007)
Dual	0.003**	−0.001	−0.001	−0.001	−0.000	−0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Top1	−0.009**	−0.017***	−0.014***	−0.008	−0.016***	−0.009***
	(0.004)	(0.004)	(0.003)	(0.005)	(0.005)	(0.003)
Tobinq	−0.002***	−0.000	−0.000	−0.001**	−0.000	−0.001**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Constant	0.049***	−0.031*	0.009	0.003	−0.069***	0.035***
	(0.013)	(0.016)	(0.018)	(0.019)	(0.017)	(0.010)
Observations	7,641	12,785	14,624	5,802	10,213	10,213
R-squared	0.444	0.394	0.365	0.427	0.421	0.371
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6. (*Continued*).

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLE	**Cod**	**Cod**	**Cod**	**Cod**	**Cod**	**Cod**
	SOEs	**Non-SOEs**	**Eastern**	**Non-eastern**	**Highagency aafeacenga gency agency agency**	**Lowagency**
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm	Firm

Note: This table shows the results of the heterogeneity test. From the table, we can see that the regression results of climate policy uncertainty on the cost of debt are significantly positively correlated in the subgroups of non-state, eastern regions, and higher agency costs. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses (Source: Author's own work).

Columns (1) and (2) of **Table 6** report the results of the SOE and non-SOE subgroup regressions respectively. Clearly, the non-SOEs group regression results are significantly positively correlated, while SOEs is not. It can be shown that the increase in financing costs for non-SOE will be stronger than SOEs when facing the risks associated with climate policy uncertainty. It supports our hypothesis.

4.2. Regional location

In China, for example, the eastern provinces are more economically developed and have significantly more manufacturing companies than other regions. As a result, carbon emissions are also higher in the eastern provinces (Wang et al., 2022). Climate policy uncertainty tends to have a greater economic effect on firms and regions with high carbon emissions, so we predict that the exacerbating effect of climate policy uncertainty on the cost of debt is more pronounced in the eastern region. We divided the sample into two groups, eastern and non-eastern, according to geographic distribution and performed separate regression analyses. The results are presented in Columns (3) and (4) of **Table 6**.

Table 6 Column (3) and (4) represent the results of grouped regressions distributed by region. It is clear that the positive correlation between climate policy uncertainty and cost of debt is more significant in the eastern subgroup. This also verifies our expectation.

4.3. Agency problems

Lenders monitor managerial misbehavior by frequently renegotiating the short-term debt of firms with high agency costs (Li, Huang, et al., 2024; Myers, 1977). And the short-term debt always has higher cost than long-term debt (Custódio et al., 2013). Therefore, we expect the exacerbating effect of climate policy uncertainty on the cost of debt to be more pronounced in firms with severe institutional problems. According to Lin et al. (2020), we use the ratio of management expenses to operating income as a proxy variable for agency cost. Using the median of management expenses to operating income as the criterion, dividing into two groups (high agency and low agency) and analyzing in separate regressions. The regression results will be shown in **Table 6**, Columns (5) and (6).

The results of the grouped regressions are shown in **Table 6**, Columns (5) and (6). The impact of climate policy uncertainty on the cost of debt is significant and positive for firms with high agency costs, while it is not significant for low agency firms. This proves that our hypothesis is valid.

5. Potential mechanism

Climate policy uncertainty significantly exacerbates the degree of financing constraints for firms, and the increase financing constraints directly limit the traditional sources of financing available to firms (Sun et al., 2024). Narrower financing options force firms to turn to more expensive and non-traditional financing options, such as the shadow banking system (Hachem, 2018). This shift indirectly but significantly increases the cost burden of financing for firms and puts them under more severe financial pressure. Thus, we expect financing constraints to be a potential mechanism by which climate policy uncertainty affects the cost of debt. Overall, climate policy uncertainty exacerbates financial constraints, which results in firms being forced to raise their cost of debt.

Following Kim et al. (2021); Lee and Wang (2021), we introduce the WW index to measure financing constraints. The WW index is proposed by Whited and Wu (2006), which involves an analysis of the firm's debt and equity structure to assess the firm's financing constraints. The higher WW index a firm has, the greater financial constraints it meets.

Table 7 presents the results of the analysis of potential mechanisms. Clearly, the results are significant in the first stage, where climate policy uncertainty leads to a rise in corporate finance constraints. In the second stage, after the introduction of the financing constraint, climate policy uncertainty raises the cost of debt for firms by affecting the financial constraint, which in turn raises the cost of. This supports the regression results as well as the hypotheses of our baseline model. Meanwhile, it provides evidence for supporting the financial friction theory applied in this study.

Table 7. Potential mechanism regressions.

	(1)	**(2)**
VARIABLE	**WW**	**Cod**
Ccpu	0.034***	0.003***
	(0.005)	(0.000)
WW		0.005***
		(0.001)
Age	0.016***	0.008***
	(0.006)	(0.001)
Size	−0.053***	−0.002***
	(0.003)	(0.000)
Soe	−0.029***	−0.004***
	(0.007)	(0.001)
Leverage	−0.196***	0.099***
	(0.017)	(0.003)

Table 7. (*Continued*).

	(1)	(2)
VARIABLE	**WW**	**Cod**
Growth	−0.050***	0.002***
	(0.005)	(0.001)
Cashflow	0.044	−0.001
	(0.038)	(0.004)
Board	−0.055***	−0.002
	(0.016)	(0.002)
Independent	−0.084	−0.001
	(0.053)	(0.007)
Dual	0.005	−0.001
	(0.007)	(0.001)
Top1	−0.045**	−0.013***
	(0.020)	(0.003)
Tobinq	−0.006**	−0.000
	(0.003)	(0.000)
Constant	0.418***	−0.001
	(0.080)	(0.012)
Observations	20,426	20,426
R-squared	0.179	0.378
Industry FE	Yes	Yes
City FE	Yes	Yes
Cluster	Firm	Firm

Note: This table represents the potential mechanism analysis of our model. Column (1) reports the first stage results that there is a significant positive relationship between climate policy uncertainty and financial constraints, which means climate policy uncertainty increases the firms' financial constraints. Column (2) shows the second-stage results, where the climate policy uncertainty still exacerbates the cost of debt after the introduction of the financing constraints. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses (Source: Author's own work).

6. Conclusion

Using annual data of Chinese A-share listed firms from 2011 to 2022 and the Chinese climate policy uncertainty index, this paper finds that climate policy uncertainty increases the cost of debt of Chinese A-share listed firms. These results are verified by a series of robustness tests, such as alternative main variable, sample adjustments, alternate model, instrumental variable approach, and propensity score matching method. In addition, heterogeneity tests represent that non-SOEs, firms in the eastern region, and firms with more pronounced agency problems are affected more by climate policy uncertainty. The results of the potential mechanism test indicate that climate policy uncertainty can increase corporate debt costs by increasing financial constraints.

In terms of future recommendations and implications, it is suggested that governments can intervene in corporate finance by controlling climate policy. Secondly, the government can broaden financing channels for enterprises at the macro level so as to better assist them in obtaining the funds needed for development under uncertainty shocks. Finally, firms are encouraged to improve their own governance to mitigate agency problems and thus avoid financing problems under uncertainty.

This study also has some limitations. We hope that future research will address these issues. We chose Chinese listed companies as our research sample. It may be considered whether our findings will be applicable to other economies as well. As the sample spans from 2011 to 2022, it may be considered whether future data will still support our findings. And also, it could be explored where there are other potential mechanisms that could affect our benchmark regression results. These questions are worthy being explorered in future studies.

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Note

1 The CSMAR database stands for China Securities Market and Accounting Research Database.

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