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The impact of climate policy uncertainty on stock price synchronicity: Evidence from China

Michelle Li [a], Xing Han [a,*], Youwei Li [b]

[a] Department of Accounting and Finance, University of Auckland Business School, Auckland 1010, New Zealand
[b] Hull University Business School, University of Hull, HU6 7RX, United Kingdom

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ABSTRACT

This paper examines the broad impact of climate policy uncertainty (CPU) on stock price synchronicity (SYN) using a newly developed news-based index. Our analysis covers listed firms in China from 2000 to 2022. We find that CPU significantly and negatively affects SYN. This negative relationship is particularly pronounced in high-polluting industries and is more evident after the Paris Agreement. These results remain robust across alternative measures of SYN.

1. Introduction

Climate risk has emerged as one of the most significant challenges of the past decade. To address these challenges, governments worldwide have introduced various measures and policies aimed at mitigating the impacts of climate change. These climate-related policies are inherently uncertain. Because such policies can substantially shape the business environment, they have the potential to influence corporate strategies (Ayed et al., 2024; Hoang, 2022; Ren et al., 2022a) and affect investor behavior in financial markets (Cepni et al., 2022; Pastor and Veronesi, 2012).

Recent papers have employed theoretical models and empirical analyzes to depict how policy uncertainty affects stock returns, as well as investigated the impact of news-based policy uncertainty on financial markets and stock prices. (Baker et al., 2016; Hsu et al., 2023; Pastor and Veronesi, 2012; Pástor and Veronesi, 2013). Hsu et al. (2023) develop a general equilibrium asset pricing model that accounts for uncertainty in firms' cash flows due to potential changes in emission regulation policies. They argue that high-polluting firms experience a greater adverse impact on their cash flows and profitability compared to low-polluting firms when environmental policies change. This increased exposure to regulatory risk results in a higher risk premium for high-polluting firms, which, in turn, affects their stock returns. Furthermore, Pástor et al. (2021) find that green stocks outperform brown stocks during periods of heightened uncertainty. Lasisi et al. (2022) also examine CPU as a predictor of stock market performance. This paper extends the nascent literature on the effects of CPU on financial markets by investigating whether it affects stock price synchronicity (SYN). Additionally, we examine whether the effect differs between firms in high-polluting and low-polluting industries. Finally, we test the impact of the Paris Agreement on the association between CPU and SYN.

Prior studies have predominantly focused on the impact of CPU on stock prices, with limited attention to SYN. Stock price synchronicity is a crucial topic in financial markets as it reflects the extent to which stock prices move together (Roll, 1988). In theory, two competing forces exist in shaping the net impact of CPU on stock price synchronicity: On the one hand, heightened climate policy

* Corresponding author at: Department of Accounting and Finance, University of Auckland Business School, 12 Grafton Road, Auckland 1010, New Zealand.

E-mail addresses: michelle.li@auckland.ac.nz (M. Li), xing.han@auckland.ac.nz (X. Han), youwei.li@hull.ac.uk (Y. Li).

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uncertainty, as a state variable, constrains the macroeconomic and business environment in which the firms operate (Pástor and Veronesi, 2013). Theory of return commonality suggests that in periods of high CPU, stock prices tend to comove in the same direction (i.e., increased comovements due to systematic factors), predicting a *positive* relation between CPU and SYN. On the other hand, uncertainty regarding climate policy could also induce firms to voluntarily disclose more unique information, generating a *negative* relation between CPU and SYN. Insights from financial constraint theory suggests that high CPU raises investor concerns and increases financing costs. To combat the adverse impact, firms tend to disclose more firm-specific information to boost the investor confidence, which leads to a reduction of the stock price synchronization. Besides, a sudden increase in CPU may expose firms, in particular high-polluting firms, to greater firm risk, prompting them to hold more cash and possibly to cut R&D investments (Gulen and Ion, 2016; Nguyen et al., 2015). Information integration of these unique firm activities into the stock price will reduce SYN. Given the two opposing forces at play, the direction of the association between CPU and SYN is an empirical issue.

Our study focuses specifically on China's climate policy uncertainty, as it provides a unique and natural institutional setting for investigating this topic. First, China has committed to several initiatives aimed at reducing its reliance on fossil fuels and transitioning towards clean energy, including setting climate goals such as achieving carbon neutrality by 2050. To meet these targets, the government closely monitors economic and climate changes, making policy adjustments more frequently. Second, as an emerging market, the Chinese stock market is more volatile than those in developed countries. Morck et al. (2000) find that stock prices tend to move together more in less developed economies than in richer ones due to stronger property rights in the latter, which encourage the acquisition of firm-specific information. This firm-specific information is more readily reflected in stock prices in developed markets. The uncertainty of climate policies in China provides an opportunity for encouraging investors to actively acquire and trade on firm-specific information, which can impact SYN.

We use the newly developed news-based CPU index by Ma et al. (2023), which employs a deep learning algorithm—the Mac-BERT model—to construct indices of Chinese climate policy uncertainty. These CPU indices are derived from text mining news articles published by major newspapers in China at national, provincial, and city levels. Using these indices, this study investigates the impact of CPU on SYN with data from China spanning 2000 to 2022. Our findings indicate that higher CPU negatively affects SYN. Further analysis reveals that this negative relationship is significant only among firms in high-polluting industries and becomes particularly pronounced following the signing of the Paris Agreement.

This paper makes several contributions to the existing literature. Firstly, it examines for the first time the impact of CPU on SYN. Previous studies have primarily focused on how CPU influences firm-level decisions such as total factor productivity (Ren et al., 2022b), dividend policy (Ayed et al., 2024), and corporate investment (Ren et al., 2022a), with no exploration of its relationship with SYN. This paper fills this gap by investigating the effect of CPU on SYN, thereby enriching the literature on the financial market's response to CPU. Secondly, while past studies on factors influencing stock price synchronicity have predominantly focused on firm-specific factors like CEO characteristics (Neifar and Ajili, 2019), ownership concentration (Gul et al., 2010), and trade credit (Liu and Hou, 2019), there is a lack of research from macro policy perspectives (Qiu et al., 2020). By examining the impact of CPU on SYN, this study extends the current discussion on the factors influencing SYN.

2. Methods

2.1. Sample selection

The sample consists of all A-share non-financial companies listed on the Shanghai and Shenzhen stock exchanges from 2000 to 2022. Data for calculating stock price synchronicity and other financial and corporate governance variables are sourced from the RESSET database. After excluding firms with special treatment (ST, PT), as well as those with missing financial and corporate governance data, the final sample comprises 27,432 firm-year observations, representing 2670 listed firms.

2.2. Variable definition

2.2.1. Measure of stock price synchronicity

To construct our dependent variable, SYN, this paper first estimates model (1). This model allows us to decompose total return variation into components tied to market and industry factors, as well as those tied to firm-specific factors.

$$R_{i,t} = \alpha_0 + \alpha_1 R_{m,t} + \alpha_2 R_{ind,t} + \varepsilon, \tag{1}$$

where $R_{i,t}$ represents firm i's stock holding return in week t, $R_{m,t}$ the average stock market return in week t, and $R_{ind,t}$ the average return of the same industry as firm i in week t. R^2 is the degree of fitness of the model (1). A higher R^2 value indicates higher price synchronicity.

Following the convention in the literature (Gul et al., 2010), we transform R^2 by taking the logarithm, as depicted in model (2), and denote it as SYN1.

$$\mathrm{SYN} = \mathrm{Ln}\left(\frac{\mathrm{R}^2}{1 - \mathrm{R}^2}\right) \tag{2}$$

To test the robustness of our results, we also augment model (1) by including lagged market and industry returns. The R^2 of the augmented model allows us to derive an alternative stock price synchronicity measure, denoted as SYN2.[1]

2.2.2. *Measurement of climate policy uncertainty*

We obtain the open-source data on the CPU index developed by Ma et al. (2023), which measures the degree of uncertainty in climate policy changes. While many studies use the US CPU index to represent global climate risk, Ma et al. (2023) develop a CPU index for China using the deep learning algorithm Mac-BERT model. This index is produced at the province and city levels with weekly, monthly, and annual frequencies spanning from 2000 to 2022. For our analysis, we utilize annual data at the province level. Specifically, we matched the annual provincial CPU levels with the headquarters' locations of the listed companies to determine the CPU levels at which the firms are located. While Xu et al. (2023) and Lin and Zhao (2023) also constructed CPU indices for China, our selection of the deep learning approach demonstrates superior model performance indicators (Ma et al., 2023).

2.3. *Research model*

In this study, we employ a panel regression model incorporating year and firm fixed effects to examine the relationship between CPU and SYN. The specification we estimate is as follows:

$$SYN_{i,t} = \beta_0 + \beta_1 CPU_{j,t} + \beta_2 Size_{i,t} + \beta_3 Lev_{i,t} + \beta_4 Cash_{i,t} + \beta_5 ROE_{i,t} + \beta_6 InstHolding_{i,t} + \beta_7 IndPer_{i,t} + \beta_8 LnBoard_{i,t} + \beta_9 Big4_{i,t} + \varepsilon, \tag{3}$$

where i is a firm, j is the province in which the listed company's headquarter is located, and t is time. In line with the previous research, we include control variables at the company level considered to affect SYN, including firm size (Size), leverage (Lev), cash holding (Cash), return on equity (ROE), institutional shareholding (InstHolding), board size (LnBoard), board independence (IndPer) and Big 4 audit firm (Big4).

3. Empirical analysis

3.1. *Summary statistics*

Table 1 presents summary statistics for the variables used in the data analysis. All non-categorical variables are winsorized at the 1st and 99th percentiles. The maximum value for SYN1(2) is 1.75(1.70), and its standard deviation is 1.03 (1.02), indicating significant variation in SYN across firms. The mean CPU index is 1.90, ranging from a minimum of 0.48 to a maximum of 3.91. Fig. 1 displays the CPU index from 2000 to 2022, showing fluctuations with an overall increasing trend in CPU over the sample period.

Table 2 displays the correlation coefficients for the key variables and control variables. The correlation coefficient between SYN and CPU is approximately -0.25. Moreover, the correlation coefficients among the variables are relatively low, indicating that multicollinearity is unlikely to be a significant concern.

3.2. *Baseline results*

We first conduct OLS regressions on model (3) to estimate the effect of CPU on SYN. All estimations control for year and firm-fixed effects. The baseline regression results are presented in Table 3. In columns (1) and (2), where only year and firm fixed effects are included, the coefficient of CPU on SYN is significantly negative at the 5 % level. This finding is consistent when SYN is measured using SYN2. When control variables are added in columns (3) and (4), the negative and statistically significant coefficient of CPU on SYN persists at the 5 % level. Overall, these results indicate that higher levels of CPU are associated with lower levels of SYN, which aligns with the theoretical arguments that heightened climate policy uncertainty improves stock price informativeness (i.e., reducing SYN), as firms tend to disclose more unique information (relative to market- and industry-wide information) to address investor concerns on climate risk.

To address the endogeneity that may arise from factors simultaneously impacting environmental policies and stock performance, we employ the U.S. CPU index, obtained from Gavriilidis (2021), as an instrumental variable and perform fixed effects two-stage least squares (FE-2SLS) analysis to mitigate endogeneity concerns. As Ren et al. (2022b) suggest, given the United States' status as the world's largest economy, the U.S. CPU index can serve as a proxy for global climate risk, which has significant implications for China's environmental policies and economic development. After mitigating endogeneity concerns, the coefficients on SYN in the FE-2SLS remain negative and statistically significant (unreported for brevity), confirming our earlier findings.

[1] Additionally, we compute SYN3 and SYN4 by running model (1) while excluding the respective company itself. The results are qualitatively similar and can be made available upon request.

Table 1
Descriptive statistics.

Variables	N	Mean	SD	Min	Median	Max
SYN1	29,039	-0.35	1.03	-3.57	-0.23	1.75
SYN2	29,039	-0.35	1.02	-3.55	-0.23	1.70
CPU	29,108	1.90	0.67	0.48	1.94	3.91
ROE	28,940	5.05	16.63	-101.74	6.63	35.93
IndPer	28,542	35.46	10.18	4.76	33.33	100.00
InstHolding	28,040	0.42	0.25	0.00	0.45	0.88
Size	29,108	22.08	1.21	19.68	21.95	25.64
Lev	29,108	46.15	20.13	6.64	46.27	94.68
Cash	29,107	17.12	11.67	1.30	14.14	58.62
Lnboard	29,104	2.41	0.34	0.00	2.40	3.78
Big4	29,108	0.04	0.19	0.00	0.00	1.00

This table reports the summary statistics for the variables used in the data analysis. Sample period is between 2000 and 2022. All variables are winsorized at 1 % and 99 % level to minimize the impact of outliers.

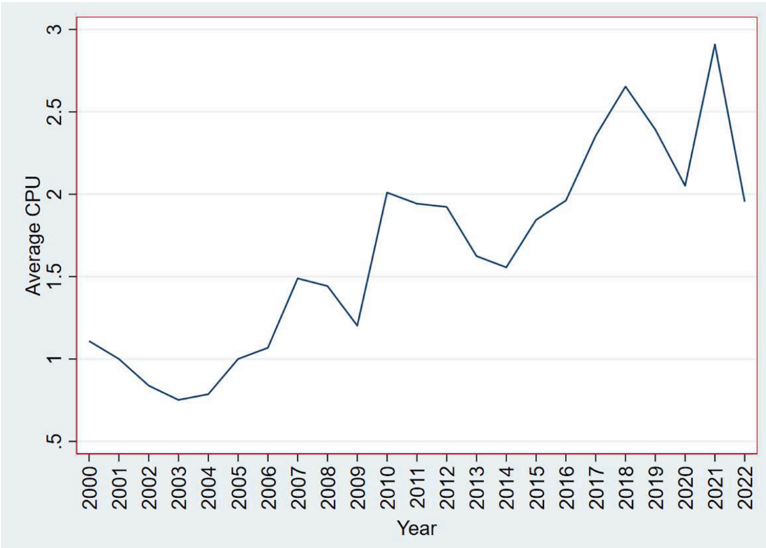

Fig. 1. Time trend of China's annual CPU.

3.3. High-polluting vs low-polluting industries

Hoang (2022) finds that the effect of CPU on corporate investment differs between high-polluting and low-polluting industries. Ayed et al. (2024) document a positive relationship between CPU and dividend payout ratio, which is less pronounced for firms in high-polluting industries. Industries with high levels of pollution are more likely to be directly targeted by climate policies, such as subsidies for greenhouse facilities in agriculture or regulations on fossil fuel combustion, impacting their stock prices accordingly. Companies emitting high levels of carbon dioxide are particularly sensitive to these policies, often responding by holding more cash or reducing investment. In contrast, firms in low-polluting industries may experience lower sensitivity to such policies. These industry-specific differences suggest that the impact of CPU on SYN may vary across industry types.

Next, we examine whether the impact of CPU on SYN differs between high-polluting and non-high-polluting industries. We partition our sample into these two categories and conduct separate analyzes for each subgroup. Following the categorization used by Ren et al. (2022b), high-polluting industries comprise of firms in mining, manufacturing, and energy production and supply.

As presented in Table 4, our results indicate that the negative impact of CPU on SYN is observed solely within high-polluting industries. Conversely, we do not observe a significant relationship between CPU and SYN in the non-high-polluting industries subgroup.

3.4. Paris Agreement

In this section, we investigate the time-varying effects of climate policy on the financial markets following the adoption of the 2016 Paris Agreement. Signed by 178 parties worldwide, the Paris Agreement represents a unified commitment to global action on climate change post-2020. Adopted during the Paris Climate Conference on 12 December 2015 and signed on 22 April 2016 at the United

Table 2
Correlation matrix.

	SYN1	SYN2	CPU	ROE	IndPer	InstHolding	Size	Lev	Cash	Lnboard	Big4
SYN1	1.000										
SYN2	0.986	1.000									
	(0.000)										
CPU	-0.253	-0.249	1.000								
	(0.000)	(0.000)									
ROE	-0.007	-0.002	0.021	1.000							
	(0.208)	(0.718)	(0.000)								
IndPer	-0.091	-0.087	0.167	0.021	1.000						
	(0.000)	(0.000)	(0.000)	(0.000)							
InstHolding	-0.002	-0.005	0.198	0.053	0.028	1.000					
	(0.699)	(0.417)	(0.000)	(0.000)	(0.000)						
Size	0.112	0.107	0.307	0.021	0.034	0.192	1.000				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
Lev	0.046	0.035	-0.056	-0.229	-0.117	0.068	0.139	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
Cash	-0.018	-0.008	0.021	0.067	0.036	0.021	-0.134	-0.136	1.000		
	(0.002)	(0.165)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
Lnboard	0.064	0.057	-0.012	-0.049	-0.366	0.150	0.116	0.185	-0.057	1.000	
	(0.000)	(0.000)	(0.038)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Big4	-0.001	-0.003	0.047	0.045	0.005	0.059	0.062	0.038	-0.001	0.023	1.000
	(0.807)	(0.577)	(0.000)	(0.000)	(0.409)	(0.000)	(0.000)	(0.000)	(0.909)	(0.000)	

This table reports the correlation coefficients among the variables used in the data analysis. p-values are reported in parentheses.

Table 3
Baseline results.

	(1) SYN1	(2) SYN2	(3) SYN1	(4) SYN2
CPU	-0.039**	-0.033*	-0.041**	-0.036**
	(0.018)	(0.018)	(0.018)	(0.018)
ROE			-0.000	0.000
			(0.000)	(0.000)
IndPer			0.001	0.000
			(0.001)	(0.001)
InstHolding			-0.108**	-0.073
			(0.053)	(0.051)
Size			0.216***	0.217***
			(0.014)	(0.014)
Lev			-0.001***	-0.002***
			(0.001)	(0.001)
Cash			-0.000	0.001
			(0.001)	(0.001)
Lnboard			0.026	0.029
			(0.027)	(0.027)
Big4			-0.016	-0.025
			(0.048)	(0.048)
Constant	-0.423***	-0.413***	-4.920***	-4.967***
	(0.050)	(0.050)	(0.297)	(0.302)
Year Fixed	Yes	Yes	Yes	Yes
Firm Fixed	Yes	Yes	Yes	Yes
R^2	0.286	0.295	0.304	0.312
N	29,039	29,039	27,432	27,432

This table presents the results from estimating the baseline model, Eq. (3). Heteroscedasticity adjusted standard errors are reported in parentheses.
*** indicates statistical significance at 1 % level.

Nations in New York, USA, the agreement was formally implemented starting from 4 November 2016. China, having ratified the agreement on 3 September 2016 through approval by the Standing Committee of the National People's Congress (NPC), has since developed numerous carbon policies in alignment with its commitments under the agreement.

The Paris Agreement signifies governments' commitment to combating climate change, potentially increasing social awareness and investor interest in clean energy while dissuading investment in high-polluting firms (Abudu et al., 2023). High-carbon-emitting companies face incentives to proactively adjust corporate policies in anticipation of future climate regulations, thereby reducing SYN. Risk-averse investors in these firms may adjust their investments, seeking company-specific information to evaluate risks and returns more accurately. These actions contribute to integrating new information into stock prices, thereby lowering SYN.

Table 4
High-polluting vs low-polluting industries.

	SYN1_high	SYN1_low	SYN2_high	SYN2_low
CPU	-0.066**	-0.029	-0.069**	-0.021
	(0.031)	(0.023)	(0.032)	(0.022)
ROE	0.001	-0.000	0.001	-0.000
	(0.001)	(0.000)	(0.001)	(0.000)
IndPer	0.001	0.000	0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
InstHolding	-0.171**	-0.070	-0.108	-0.051
	(0.083)	(0.066)	(0.081)	(0.065)
Size	0.201***	0.214***	0.201***	0.213***
	(0.024)	(0.018)	(0.024)	(0.018)
Lev	-0.002**	-0.001	-0.002**	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Cash	0.001	-0.001	0.002**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Lnboard	0.019	0.020	0.022	0.023
	(0.046)	(0.034)	(0.045)	(0.034)
Big4	-0.029	-0.004	-0.037	-0.010
	(0.070)	(0.064)	(0.068)	(0.064)
Constant	-4.646***	-4.805***	-4.654***	-4.816***
	(0.507)	(0.385)	(0.514)	(0.393)
Year fixed	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	Yes	Yes
R2	0.284	0.315	0.293	0.323
N	9654	17,778	9654	17,778

This table reports the results from estimating the baseline model, Eq.(3) when the full sample is divided into high-polluting industries and low-polluting industries. Heteroscedasticity adjusted standard errors are reported in parentheses.
*** indicates statistical significance at 1 % level.

Table 5
Paris Agreement.

	SYN1_post	SYN1_pre	SYN2_post	SYN2_pre
CPU	-0.525***	0.116***	-0.526***	0.126***
	(0.017)	(0.018)	(0.017)	(0.018)
ROE	-0.000	-0.001*	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
IndPer	-0.003*	-0.006***	-0.004**	-0.007***
	(0.002)	(0.001)	(0.002)	(0.001)
InstHolding	0.303*	-0.160***	0.284*	-0.172***
	(0.160)	(0.050)	(0.159)	(0.049)
Size	-0.188***	0.009	-0.208***	0.015
	(0.031)	(0.017)	(0.032)	(0.017)
Lev	-0.003**	-0.003***	-0.003**	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Cash	0.000	0.002*	0.001	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Lnboard	0.095*	-0.162***	0.103*	-0.160***
	(0.055)	(0.041)	(0.055)	(0.041)
Big4	-0.016	0.063	-0.049	0.045
	(0.102)	(0.080)	(0.099)	(0.078)
Constant	4.704***	0.345	5.155***	0.220
	(0.722)	(0.352)	(0.728)	(0.355)
Year fixed	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	Yes	Yes
R2	0.074	0.011	0.076	0.014
N	13,792	13,640	13,792	13,640

This table reports the results from estimating the baseline model, Eq. (3) when the full sample is divided into pre- and post- 2016 period. Heteroscedasticity adjusted standard errors are reported in parentheses.
*** indicates statistical significance at 1 % level.

Therefore, this paper designates 2016 as the policy intervention year to examine the impact of events on the relationship between CPU and SYN. We partition our sample into two periods: pre-2016 and post-2016 and analyze the relationship between CPU and SYN. Table 5 presents the estimation results of this analysis. Consistently, the results indicate a negative relationship between CPU and SYN after 2016, and a positive relationship before 2016, both statistically significant at the 1 % level. The sharp contrast between the pre- and post-2016 periods can be attributed to the increased social awareness and heightened investor interest following the Paris

Agreement. This global accord brought climate change to the forefront and significantly influenced investor perceptions of climate-related risks and opportunities. As a result, the importance and dynamics of CPU evolved, as evidenced by our results demonstrating the time-varying nature of the relationship between CPU and SYN.

4. Conclusion

In conclusion, this study investigates the impact of climate policy uncertainty (CPU) on stock price synchronicity (SYN) using a comprehensive dataset of Chinese non-financial firms from 2000 to 2022. Our findings reveal several key insights. Firstly, we observe a significant negative relationship between CPU and SYN, indicating that heightened uncertainty in climate policies tends to reduce the co-movement of stock prices across firms. This effect is particularly pronounced in high-polluting industries, underscoring the sector-specific impacts of climate policy uncertainty. Secondly, our analysis highlights the time-varying nature of this relationship, with distinct patterns emerging before and after the 2016 Paris Agreement. Specifically, post-2016, there is a stronger negative association between CPU and SYN, suggesting heightened sensitivity to climate policy developments following the agreement's implementation.

These results contribute to the literature by enriching our understanding of how climate policy uncertainty influences financial markets, particularly in emerging economies like China. Our findings suggest that investors and policymakers should consider the differential impacts across industries and over time when assessing the financial implications of climate policy uncertainty. Future research could further explore the mechanisms through which firms respond to such uncertainties and the implications for corporate strategies and market dynamics.

CRediT authorship contribution statement

Michelle Li: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Validation. **Xing Han:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Youwei Li:** Writing – review & editing, Supervision, Project administration, Investigation.

Declaration of interest

We have no potential competing interests, including employment, consultancies, stock ownership, honoraria, paid expert testimony, patent applications/registrations, and grants or other funding.

Data availability

Data will be made available on request.

Appendix: Variable definition

Variable names	Definitions
SYN1	Logarithmic transformation of R2 for the market model in Eq. (1), computed as Ln [R2/(1 − R2)]
SYN2	Logarithmic transformation of R2 for the market model in Eq. (1), augmented by including lagged market and industry returns
CPU	Climate policy uncertainty indices, obtained from Ma et al. (2023)
ROE	Return on equity, measured as the net profit scaled by total equity
IndPer	Board independence, measured as the number of independent directors to board size
InstHolding	Institution investor's shareholding percentage
Size	Firm size, measured as the natural logarithm of total assets
Lev	Debt ratio, measured as the ratio of liabilities to total assets
Cash	(cash+cash equivalents+trading financial assets)/total assets
Inboard	Board size, measured as the natural log of the total number of board directors
Big4	Dummy variable, equalling 1 when the auditor is a Bit 4 accounting firm and 0 otherwise.

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