When Climate Policies Waver: Firms, Debt, and the Investment-Financing Maturity Mismatch

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Abstract

Addressing the mismatch between corporate investments and financing maturities is essential for safeguarding against systemic financial risks. In this study, we investigate the impact of climate policy uncertainty (CPU) on corporate investment-financing maturity mismatch using data from Chinese A-share companies from 2007 to 2022. Findings indicate that increased CPU exacerbates the mismatch, prompting firms to rely more on short-term borrowing to finance long-term investments. CPU deteriorates the financing environment and amplifies information asymmetry, thereby intensifying the mismatch. Firms with weaker climate resilience are particularly vulnerable. Our results offer significant insights into the financial risks posed by CPU.

Keywords: Climate policy uncertainty; Maturity mismatch; Short-term debt; Long-term investments.

1. Introduction

Governments worldwide have implemented climate policies to mitigate the impact of extreme climate events. However, the timing, intensity, and pace of policy implementation are uncertain due to political cycles, international cooperation dynamics, and technological path dependencies. Such climate policy uncertainty (CPU) increases the difficulty of long-term planning and adversely affects firm performance (Pankratz et al., 2023), prompting firms to seek stable, long-term financing. China, the world's largest carbon emitter, is transitioning from its "dual carbon" goals of peaking carbon emissions by 2030 and reaching carbon neutrality by 2060 to detailed local policies. Due to changing regulations, CPU in China is dynamic and complex. Moreover, compared to developed economies, China's capital market remains underdeveloped, with bank credit dominating corporate external financing (Liu et al., 2018), resulting in a debt-driven investment model (Campello et al., 2011). Banks provide short-term credit for risk control, which mismatches with enterprises' long-term capital needs for green transformation. Firms have to use short-term financing to meet their long-term investment demands, leading to maturity mismatches. This practice contradicts maturity matching theory's emphasis on aligning financing and investment horizons (Morris, 1976; Myers, 1977). This strategy temporarily addresses financing needs and alleviates liquidity pressures (Campello et al., 2011). However, it exposes firms to greater liquidity risks (Custódio et al., 2013), which could lead to broken capital chains (Gopalan et al., 2014). Given the evolving climate policies, this structural mismatch has become increasingly prominent, posing several practical challenges. Policymakers struggle to balance carbon transition goals with corporate liquidity. The bank-dominated credit system, which lacks dynamic adjustment mechanisms, rigidifies financing structures. Furthermore, firms struggle to optimise their financial strategies to cope with climate-related risks. The CPU–maturity mismatch relation is particularly relevant to China. This study not only expands the traditional financial intermediation theory's application boundary by examining the impact of institutional uncertainty on credit allocation but also offers practical implications for policymakers and corporate managers.

Climate policy entails substantial externalities and long-term trade-offs between emission reduction and economic development. It triggers a systemic reassessment of policy discount rates in financial markets, reshaping risk pricing and influencing firms' investment-financing maturity structures. Tightening credit standards, reducing long-term loan supply, and using short-term instruments to monitor firms' financial conditions and performance help banks mitigate long-term risk exposure during uncertain policy transitions (Rajan & Zingales, 1998; Cheng & Milbradt, 2012). Due to their underdeveloped financial system, Chinese banks are unable to fully adjust interest rates to consider rising climate-related risks (Du & Qian, 2022). Therefore, banks can only use credit rationing to limit exposure, which reduces long-term financing and forces firms to passively adopt maturity mismatches in response to external uncertainty (Fan et al., 2012; Cortina et al., 2018). Some state-owned enterprises and leading firms receive implicit government guarantees and preferential access to long-term loans, whereas smaller and private firms do not (Liu et al., 2018). Typical firms' access to long-term credit is constrained by factors such as ownership structure, firm size, and collateral availability, thereby narrowing their financing options. Moreover, CPU increases volatility in expected asset returns, causing investors to shorten investment horizons. This raises the liquidity premium on long-term instruments, increasing financing costs and limiting firm access to long-term capital.

Building on this foundation, we argue that CPU may exacerbate firms' maturity mismatches by (1) deteriorating their external financing environment and (2) amplifying information asymmetries amongst stakeholders. On the one hand, increased uncertainty significantly increases firms' financing difficulties (Mo & Liu, 2023; Ren et al., 2022a). Transaction cost theory (Ghoshal & Moran, 1996) posits that CPU raises firms' institutional and informational costs in securing capital, creating structural frictions. These frictions aggravate financing barriers and marginal borrowing costs, disrupting debt maturities. Banks tend to tighten credit standards during periods of greater assessment uncertainty, particularly for long-term lending. This structural financing constraint hinders firms' ability to align their debt maturities with their investment horizons, resulting in maturity mismatches (Si et al., 2023). On the other hand, CPU intensifies information asymmetry between firms and external financial agents (Ge & Zhang, 2025), shortening debt maturity (Custódio et al., 2013). Signalling theory (Spence, 1978) suggests that firms can enhance their access to financing by disclosing credible information about their financial soundness and creditworthiness (Chen et al., 2023). As uncertainty increases, assessing firm-level risks becomes more expensive and difficult, thereby raising monitoring costs and the probability of misjudgement (Lin & Dong, 2023). In response, creditors demand higher risk premiums or shorter loan maturities. Meanwhile, firms under increasing financial pressure may engage in earnings management to accelerate the recognition of future income (Merchant, 1990), which lowers the credibility of financial disclosures (Ghosh & Olsen, 2009) and impairs lenders' ability to assess long-term solvency (Bhattacharya et al., 2012). Information asymmetry worsens as earnings quality declines, limiting access to long-term credit and increasing firms' reliance on short-term borrowing to fund long-term investments (Zhang et al., 2024).

Existing studies have not fully understood the impact of CPU on corporate maturity mismatches; therefore, we analyse data from Chinese A-share listed firms (2007–2022). We show that by worsening the financing environment and increasing information asymmetry, rising CPU significantly increases firms' reliance on short-term borrowing for long-term investment. This effect is stronger in firms with lower green innovation, insufficient climate-related disclosure, weaker environmental, social, and governance (ESG) performance, and higher supply chain concentration. Furthermore, maturity mismatches amplify CPU's adverse effects on bond default risk and earnings volatility.

This study makes several significant contributions. First, although prior studies focused on the impact of government actions, bank liquidity management, and corporate ownership structure on firm financing mismatch (e.g., Li et al., 2024a; Ma et al., 2022; Li et al., 2024b), few have examined how institutional policy shifts reshape firms' financing structures (Wang & Jing, 2025; Tang et al., 2025). In particular, climate-related uncertainty is especially overlooked. Incorporating CPU into firms' intertemporal financing decisions, we draw on transaction cost and signalling theories to show how CPU intensifies financing frictions and information asymmetry, thereby increasing the likelihood that firms will use short-term debt to fund long-term investments. This expands our understanding of how macro-level institutional shifts affect firms' debt maturity structures. Second, we extend the literature on CPU and corporate behaviour, while refining the applicability of maturity matching and financial intermediation theories under institutional uncertainty. Most studies have examined CPU's effects on firm value, productivity, investment, and innovation, and earnings management (Azimli, 2023; Ren et al., 2022b; Huang & Sun, 2024; Tran, 2025), with limited attention paid to its risk implications for maturity mismatches. Amongst the few relevant studies, Chen et al. (2024) conceptualise CPU as a firm-level signal that influences risk preferences and debt management, focusing on internal governance. In contrast, we adopt an institutional pressure perspective and develop an analytical framework linking macropolicy uncertainty, external financing pressure, maturity structure, and investment decisions, within the context of China's bank-dominated financial system. Finally, based on dynamic capability theory (Eisenhardt & Martin, 2000), we explore how firm-level differences in green innovation, information disclosure, and supply chain structure influence responses to CPU-induced maturity mismatches. Based on these insights, we propose a three-dimensional policy framework to improve climate resilience and guide managers and policymakers.

2. **Data and methodology**

2.1. *Data and variables*

We use panel data from Chinese A-share listed firms from 2007 to 2022 to identify the transmission channels through which CPU influences corporate investment and financing decisions. Listed firms have standardised disclosure practices, financing behaviour, and policy responsiveness. Due to stronger governance and regulatory oversight, listed firms may experience less severe maturity mismatches than non-listed small- and medium-sized enterprises. However, if our results were to reveal a significant positive impact of CPU even in this more transparent group, the observed effects in listed firms would likely be conservative estimates. This, in turn, would imply that our findings are generalisable. Financial and firm-level data are obtained from the China Stock Market & Accounting Research (CSMAR) database.[1] Financial firms, firms marked ST/PT due to abnormal operations, firms with asset-liability ratios above one or below zero, and firms with missing key variables are excluded from the analysis. The final sample comprises 3,540 firms, yielding 36,067 firm-year observations.

Our main dependent variable is the investment-financing maturity mismatch, proxied by short-term financing for long-term investment (SFLI), following Wang *et al.* (2021a). The key independent variable is Chinese climate policy uncertainty (CPU), measured using Ma et al.'s (2023) national-level news-based index.

Following Fan et al. (2012) and Wang et al. (2021b), we incorporate a set of control variables at both the firm and national levels. Firm-level variables include firm size (*Size*), leverage ratio (*Lev*), firm age (*Age*), cash ratio (*Cashflow*), return on assets (*ROA*), revenue growth rate (*Firm_Growth*), ownership concentration (*Top1*), CEO duality (*Dual*), and executive compensation (*Salary*). Macroeconomic controls include national economic growth (*GDP_Growth*) and monetary policy conditions (*M2_Growth*). Appendix A presents the definitions of these variables.

Table 1 shows summary statistics. The median and mean *SFLI* scores are −0.065 and −0.073, respectively. The binary indicator *SFLI_dum* has a mean of 0.253, suggesting that maturity mismatch behaviour is relatively common amongst Chinese firms during the sample period. These results are broadly consistent with those reported by Wang et al. (2021b). The mean and standard deviation of the CPU index are 2.441 and 0.438, respectively, indicating substantial variability throughout the sample period.

[Insert Table 1 Here]

2.2. *Baseline econometric model*

[1] Data source: https://data.csmar.com

The following fixed-effect regression model is constructed to examine the relation between CPU and firms' investment-financing maturity mismatch:

$$SFLI_{i,t} = \alpha_0 + \beta_1 CPU_{t-1} + \gamma' X_{i,t} + \lambda' Z_t + Firm_i + \varepsilon_{i,t} \quad (1)$$

where i and t represent index firms and years, respectively. CPU_{t-1} represents the CPU level in previous period, given the potential lagged effects of CPU. $SFLI_{i,t}$ denotes the degree of *SFLI* in firm i in the current period. $X_{i,t}$ and Z_t are matrices of firm-level and national-level control variables, respectively.

To prevent the interference of unobservable firm-level factors, firm fixed effects ($Firm_i$) are controlled. We do not include year-fixed effects in the baseline model to avoid perfect collinearity with the CPU index. To avoid omitted variable bias, we control for macroeconomic variables, such as economic growth (*GDP_Growth*) and monetary policy (*M2_Growth*). Standard errors are clustered at the firm level to account for potential heteroskedasticity.

3. Empirical results

3.1. Baseline regression

Columns (1) and (2) of Table 2 present the effect of lagged climate policy uncertainty (*L.CPU*) on *SFLI*, controlling for firm fixed effects. Column (2) adds firm- and macro-level control variables, with the coefficient on *L.CPU* remaining significantly positive (0.029***), suggesting that higher CPU increases firms' reliance on SFLI dependence. A one standard deviation increase in CPU results in a 9.1% increase in *SFLI* (0.029× 0.438/0.140), making the effect economically significant. Columns (3) and (4) replace the dependent variable with short-term debt (*DebtCL_Asset*) and long-term debt (*DebtNCL_Asset*) to total assets, showing that the CPU significantly increases and decreases short- and long-term debt, respectively, confirming the baseline result.

[Insert Table 2 Here]

3.2. Endogeneity issue

We lagged the CPU index to reduce reverse causality; however, omitted variables and selection bias may still cause endogeneity. To further address these issues, we adopt the instrumental variables (IV), entropy balancing, and difference-in-differences (DiD) approaches. First, Gavriilidis's (2021) US CPU index is used as an instrument for China's CPU. Given the global nature of climate risks, US policy uncertainty is likely to correlate with China's CPU through international spillovers, thereby satisfying instrument relevance while remaining exogenous to Chinese firms' maturity decisions. IV estimates in Columns 1 and 2 of Table 3 confirm the robustness of our baseline findings. Second, we employ entropy balancing (Hainmueller, 2012), which mitigates selection bias by creating matched samples of firms with and without SFLI, with the results (Column 3) remaining robust. Finally, we adopt a DID approach using China's signing of the Paris Agreement in April 2016 as an exogenous shock. The introduction of related policies may have increased domestic CPU (Dai & Zhu, 2024), and results in Columns 4 and 5 indicate an intensified CPU effect post-Agreement, supporting a causal interpretation.

[Insert Table 3 Here]

3.3. *Further robustness tests*

We further perform several robustness checks to ensure the robustness of our findings. First, following Chen et al. (2023), we construct an alternative SFLI measure (*SFLI2*), defined as the difference between the ratios of short-term liabilities and short-term assets, where a higher value indicates a greater degree of maturity mismatch.

Second, we use an alternative CPU index (*CPU_Lee*) and a Climate Uncertainty index (*CU_Lee*), both by Lee & Cho (2023), which are derived from climate-related Twitter data, to mitigate potential bias from traditional media sources (Qin et al., 2018). Third, we re-estimate the model by clustering at the firm-year level, excluding the 2008–2009 global financial crisis period, and including several macro-level control variables: the Chinese Economic Policy Uncertainty index (*EPU*)[2], the Chinese regional economic development level (*GDP_prov*)[3] and the marketisation index (*Market_index*)[4]. Finally, we re-estimate by (1) adding a linear time trend term (*Time_Trend*) to the baseline regression and (2) changing the fixed effects specification by manually introducing year dummies to address potential bias from unobserved time trends in the long-panel data. The robustness checks in Table 4 confirm the statistical significance of our baseline results.

[Insert Table 4 Here]

3.4. *Heterogeneity analysis*

Firms respond heterogeneously to CPU shocks largely due to climate resilience. According to dynamic capability theory, firms can develop new adaptive capacities by integrating, building, and reconfiguring internal and external resources to respond to rapidly changing environments (Eisenhardt & Martin, 2000). Firms with stronger adaptive capacity can better transform uncertainty into investment opportunities, thereby enhancing the value of real options (Bird et al., 2023). We measure firms' climate resilience across four key dimensions: green innovation capacity, climate-related information disclosure, ESG performance, and supply chain resilience. Specifically, firms with greater green innovation capacity – as evidenced by more extensive green patent holdings – can proactively adapt to CPU by creating climate-aligned technological

[2] Made available by Baker *et al.* (2013) at: https://www.policyuncertainty.com/scmp_monthly.html
[3] Available at: https://data.stats.gov.cn/easyquery.htm?cn=E0103
[4] Made available by Wang *et al.* (2021a) at: https://cmi.ssap.com.cn/

advantages. Robust climate-related disclosures reduce information asymmetry and help firms manage stakeholder expectations effectively under uncertainty. Superior ESG performance further reflects a firm's comprehensive capacity to respond strategically to climate risks. Additionally, firms with lower supply chain concentration can weather CPU-related supply shocks and stay competitive. Table 5, the coefficients on interaction terms indicate that under CPU shocks, climate-resilient firms have lower levels of maturity mismatch.

[Insert Table 5 Here]

3.5. Mechanism analysis

The CPU fundamentally reshapes the external environment, worsening firms' financing conditions and exacerbating information asymmetry amongst stakeholders. We examine two key mechanisms through which CPU intensifies maturity mismatch: financing constraints and information asymmetry.

First, we measure firms' access to long-term credit using four proxies: Firms' exposure to banks' liquidity hoarding (*LWLH*)[5], the *KZ* index for overall financing constraints, financial distress (*Z_dum*), and long-term debt accessibility (*LA*). Columns (1)–(4) in Table 6 indicate that CPU significantly increases firms' exposure to bank liquidity hoarding, financing difficulties, and financial distress risks, thereby reducing their access to long-term funding and exacerbating maturity mismatch.

Second, we assess information asymmetry through disclosure and earnings quality proxies: the information asymmetry (ASY) index, accrual-based earnings management indicators (*Res_DD, Res_Jones*), and disclosure opacity scores, and a textual indicator of management climate-related disclosure (*MCA_firm*)[6]. Columns (5)–(9) of Table 6 show that the CPU significantly increases firms' ASY index, earnings management indicators and disclosure opacity scores, and reduces management's disclosure of climate-related information, thereby worsening their information environments and increasing reliance on SFLI.

[Insert Table 6 Here]

3.6. Additional analysis: Economic implications

We examine how CPU-induced maturity mismatch affect corporate risk exposure. We argue

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[5] Since the firm-level liquidity hoarding indicator (*LWLH*) is based on loan data available only from 2012, this mechanism analysis spans the period from 2012 to 2022. To account for any bias introduced by omitting the early years, we re-ran the baseline regressions on this sub-sample. The results remain significant, confirming that our main findings are robust to the sample period. Appendix D includes detailed results.

that while CPU tightens financing conditions and compresses profit margins (Liu et al., 2023), firms with high short-term debt face greater liquidity pressure and refinancing shocks, elevating their default risk (Liu et al., 2021). Moreover, CPU increases market volatility and lowers earnings visibility (Liu et al., 2025). When firms rely on short-term debt to fund long-term investments, refinancing uncertainty further amplifies earnings fluctuations – operational risk (Aysun, 2020). We use expected default probability (*EDF*) as the proxy for default risk (Abinzano et al., 2020), where higher values indicate a greater default likelihood. Operational risk is proxied by the standard deviation of industry-adjusted return on equity (*ROE_risk02*), with higher values indicating more volatile earnings. Table 7 shows that CPU raises both risks and their interactions with SFLI are significantly positive, suggesting that maturity mismatch increase firms' vulnerability to risks under CPU.

[Insert Table 7 Here]

4. **Conclusion**

This study highlights the impact of CPU on corporate investment-financing maturity mismatches in China. Using data from 2007 to 2022, we demonstrate that rising CPU increases firms' reliance on short-term borrowing for long-term investment (SFLI), primarily by tightening credit access and worsening information asymmetry. These effects are more pronounced in firms with limited green innovation, insufficient climate-related disclosure, weaker ESG performance, or higher supply chain concentration – indicators of lower climate resilience. We further find that SFLI amplifies the negative effects of CPU on default risk and earnings volatility, indicating that maturity mismatch increases the vulnerability of firms to climate uncertainty. To mitigate the negative effects of CPU on corporate behaviour, we propose a three-fold policy framework that spans firm, institutional, and government dimensions.

Firms are encouraged to enhance their resilience at the micro level by investing in green technologies and innovations. To improve adaptive capacity, reduce information asymmetries amongst financial institutions, and increase long-term credit access, voluntary environmental disclosure should be adopted. Furthermore, specialised training programmes can enhance managers' ability to manage climate-related financial risks and strengthen internal risk management systems (Huang et al., 2024).

The disclosure infrastructure must be improved at the intermediary level. Moreover, industry associations and stock exchanges should unify climate-related reporting standards to improve ESG transparency and comparability. This will not only increase the efficiency of capital market resource allocation but also alleviate financing difficulties arising from information asymmetry, particularly in bank-dominated financial systems.

At the macro level, policymakers and financial regulators should provide stronger policy support – such as credit guarantees or fiscal subsidies to mitigate financing pressure in uncertain environments. They should encourage the restructuring of short-term corporate debt into longer-term, more stable financing arrangements to protect corporate liquidity and bolster the financial system's resilience to climate-related policy transitions, ultimately facilitating a smoother green transition.

Funding statement

This study is supported by National Natural Science Foundation of China (Grant No. 71963001), Ministry of Education of the People's Republic of China Humanities and Social Sciences Youth Foundation (Grant No. 24XJC790007), and the Graduate Innovation Program of China–ASEAN School of Economics, Guangxi University, Grant No. ZX020800343240012024.

CRediT authorship contribution statement

Chunzhi Tan: Writing – review & editing, Supervision, Resources, Methodology, Investigation, Funding acquisition, Conceptualization. **Junjie Liu:** Writing – original draft, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Junfeng Ma:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Conceptualization. **Bin Liu:** Writing – original draft, Software, Methodology, Investigation, Data curation. **Boru Ren:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Conceptualization.

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Tables

Table 1. Descriptive statistics

Variable	N	Mean	SD	Min	P25	Median	P75	Max
SFLI	36,067	–0.073	0.140	–0.554	–0.140	–0.065	0.001	0.374
SFLI_dum	36,067	0.253	0.435	0.000	0.000	0.000	1.000	1.000
DebtCL_Asset	36,067	0.355	0.182	0.042	0.215	0.336	0.472	0.922
DebtNCL_Asset	34,974	0.091	0.103	0.000	0.015	0.050	0.135	0.485
CPU	36,067	2.441	0.438	1.363	2.213	2.341	2.843	3.200
CPU_Lee	32,548	1.497	1.807	0.102	0.259	0.787	1.516	5.655
CU_Lee	32,548	1.399	1.234	0.190	0.511	0.958	1.471	3.952
Size	36,067	22.196	1.323	19.302	21.272	22.014	22.924	27.07
Age	36,067	2.208	0.739	0.000	1.609	2.303	2.833	3.332
Leverage	36,067	0.443	0.209	0.055	0.280	0.437	0.594	0.984
ROA	36,067	3.492	6.583	–28.850	1.270	3.550	6.540	20.050
Cashflow	36,067	0.006	0.081	–0.244	–0.030	0.004	0.039	0.468
Top1	36,067	34.180	14.859	8.430	22.600	31.970	44.410	74.660
Dual	36,067	0.264	0.441	0.000	0.000	0.000	1.000	1.000
Salary	36,067	0.004	0.448	–0.014	0.000	0.001	0.002	85.015
Firm_Growth	36,067	0.176	0.448	–0.633	–0.028	0.108	0.271	3.082
GDP_Growth	32,628	0.106	0.047	0.030	0.073	0.102	0.131	0.231
M2_Growth	32,628	0.124	0.046	0.081	0.090	0.110	0.144	0.284

Note: Continuous variables are winsorized at the 1% level to mitigate the influence of outliers.

Table 2. The impact of climate policy uncertainty on short-term borrowing for long-term investments

Variable	(1)	(2)	(3)	(4)
	SFLI	*SFLI*	*DebtCL_Asset*	*DebtNCL_Asset*
L.CPU	0.007***	0.029***	0.015***	–0.015***
	(3.718)	(9.608)	(8.983)	(–8.266)
Size		–0.021***	–0.027***	0.022***
		(–9.212)	(–11.908)	(9.265)
Age		–0.013***	0.006**	–0.005
		(–3.900)	(2.165)	(–1.555)
Leverage		0.099***	0.783***	0.236***
		(10.269)	(93.996)	(27.186)
ROA		–0.010***	0.000	–0.000***
		(–48.969)	(1.568)	(–2.876)
Cashflow		–0.611***	0.008*	–0.013***
		(–50.178)	(1.851)	(–2.894)
Top1		0.000***	–0.000*	0.000
		(3.007)	(–1.866)	(1.556)
Dual		0.003	0.001	–0.001
		(1.377)	(0.706)	(–0.620)
Salary		–0.001***	0.001***	0.001***
		(–13.034)	(13.817)	(8.300)
Firm_Growth		–0.053***	0.003***	–0.004***
		(–20.223)	(2.756)	(–3.183)
GDP_Growth		0.318***	0.064***	–0.060***
		(16.039)	(5.411)	(–5.024)
M2_Growth		–0.042	0.042**	–0.037*
		(–1.568)	(2.100)	(–1.785)
Constant	–0.094***	0.305***	0.546***	–0.462***
	(–18.977)	(6.588)	(11.538)	(–9.168)
Number of obs.	31,831	28,554	28,554	27,799

Adjusted R^2	0.093	0.502	0.897	0.698
Firm_FE	Yes	Yes	Yes	Yes

Notes: Values in parentheses are t-values, with standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Regression results addressing endogeneity

Variable	(1) *L .CPU*	(2) *SFLI*	(3) *SFLI*	(4) *CPU*	(5) *SFLI*
L.CPU_US	0.163***				
	(110.979)				
L.CPU		0.161***	0.035***		0.016***
		(11.719)	(9.693)		(3.833)
PAPost				0.089***	
				(32.770)	
PAPost × *L.CPU*					0.026***
					(4.895)
Size	0.008***	–0.023***	–0.008***	0.091***	–0.020***
	(4.231)	(–10.087)	(–5.419)	(21.933)	(–8.838)
Age	–0.091***	–0.022***	–0.015***	0.299***	–0.012***
	(–20.359)	(–6.269)	(–4.567)	(57.134)	(–3.207)
Leverage	0.000	0.102***	0.114***	–0.229***	0.097***
	(0.047)	(10.420)	(17.671)	(–14.409)	(10.004)
ROA	–0.000	–0.010***	–0.006***	–0.000	–0.010***
	(–1.539)	(–47.922)	(–50.545)	(–1.115)	(–49.043)
Cashflow	–0.026*	–0.604***	–0.326***	–0.187***	–0.612***
	(–1.707)	(–48.546)	(–33.706)	(–12.602)	(–50.261)
Top1	–0.000***	0.000***	0.000***	0.001***	0.000***
	(–3.445)	(3.356)	(3.733)	(3.915)	(3.083)
Dual	–0.004	0.004	0.007***	0.016***	0.004
	(–1.171)	(1.599)	(3.144)	(3.529)	(1.475)
Salary	0.006***	–0.002***	0.000	0.003***	–0.001***
	(56.362)	(–15.716)	(0.329)	(5.919)	(–12.501)
Firm_Growth	–0.016***	–0.050***	–0.030***	0.013***	–0.053***
	(–5.698)	(–18.829)	(–16.139)	(4.170)	(–20.129)
GDP_Growth	–3.743***	0.756***	0.354***	2.758***	0.330***
	(–219.204)	(15.488)	(16.353)	(79.222)	(15.479)
M2_Growth	–5.405***	0.649***	0.104***	–5.496***	–0.095***
	(–301.281)	(8.952)	(3.384)	(–153.721)	(–3.337)
Constant	3.267***		–0.028	0.198**	0.329***
	(82.350)		(–0.799)	(2.198)	(6.731)
Number of obs.	28,554	28,554	28,554	32,385	28,554
Adjusted R^2	0.767	0.414	0.569	0.783	0.502
Firm_FE	Yes	Yes	Yes	Yes	Yes
Underidentification test (p)		0.000			
Weak identification test		1917.043			
10% maximal IV size		16.38			

This table addresses endogeneity concerns using three empirical methods. Column (1) shows the first-stage regression using the US CPU index (Gavriilidis, 2021) as an instrument for Chinese CPU. Column (2) shows the second-stage IV estimation. Column (3) reports entropy balancing results, comparing matched firms with (*SFLI_dum* = 1) and without (*SFLI_dum* = 0) maturity mismatches to control for intrinsic differences. The matching results are presented in Appendix B. Column (4) tests whether the CPU increased after the 2016 Paris Agreement, where *PAPos*t = 1 from 2016 onwards (Liu et al.,2024). Column (5) includes the *CPU* × *PAPost* interaction term for difference-in-differences estimation. Values in parentheses are t-values, with standard errors clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Results of robustness tests

Variable	(1) *SFLI2*	(2) *SFLI*	(3) *SFLI*	(4) *SFLI*	(5) *SFLI*	(6) *SFLI*	(7) *SFLI*	(8) *SFLI*
L.CPU	0.014***			0.029***	0.031***	0.017***	0.027***	0.015***
	(3.320)			(3.472)	(9.963)	(4.238)	(9.003)	(2.955)
L.CPU_Lee		0.026***						
		(13.207)						
L.CU_Lee			0.034***					
			(11.486)					
EPU						0.003***		
						(4.763)		
lnGDP_prov						0.018***		
						(2.955)		
Market_index						0.002		
						(1.222)		
Time_Trend							0.003***	
							(5.281)	
Size	–0.027***	–0.028***	–0.029***	–0.021***	–0.024***	–0.022***	–0.023***	–0.019***
	(–4.957)	(–10.783)	(–11.022)	(–4.415)	(–9.950)	(–9.716)	(–9.783)	(–9.014)
Age	0.026***	–0.039***	–0.043***	–0.013	–0.012***	–0.031***	–0.031***	–0.026***
	(3.327)	(–8.900)	(–8.941)	(–1.481)	(–3.276)	(–7.153)	(–6.457)	(–6.020)
Leverage	–0.138***	0.126***	0.130***	0.099***	0.115***	0.103***	0.105***	0.081***
	(–6.354)	(11.838)	(12.044)	(3.597)	(11.026)	(10.599)	(10.644)	(9.156)
ROA	–0.002***	–0.009***	–0.009***	–0.010***	–0.010***	–0.010***	–0.010***	–0.010***
	(–5.547)	(–46.109)	(–45.886)	(–28.064)	(–48.152)	(–48.872)	(–48.714)	(–54.452)
Cashflow	–0.369***	–0.598***	–0.599***	–0.611***	–0.608***	–0.610***	–0.610***	–0.608***
	(–29.430)	(–46.472)	(–46.706)	(–20.915)	(–48.724)	(–50.143)	(–50.030)	(–52.672)
Top1	–0.001*	0.000***	0.000***	0.000**	0.000***	0.000***	0.000***	0.000**
	(–1.914)	(2.912)	(2.936)	(2.823)	(3.109)	(2.977)	(2.919)	(2.238)
Dual	–0.004	0.004*	0.004*	0.003	0.005*	0.003	0.003	0.004
	(–0.787)	(1.742)	(1.655)	(1.445)	(1.838)	(1.322)	(1.299)	(1.548)
Salary	–2.186***	–0.001***	–0.001***	–0.001**	–0.002***	–0.001***	–0.001***	–0.001***
	(–2.894)	(–11.505)	(–11.092)	(–2.845)	(–14.908)	(–12.004)	(–13.096)	(–14.182)
Firm_Growth	–0.004	–0.053***	–0.053***	–0.053***	–0.053***	–0.053***	–0.053***	–0.050***
	(–1.383)	(–18.301)	(–18.378)	(–15.945)	(–19.041)	(–20.229)	(–20.326)	(–19.697)
GDP_Growth	0.011	0.165***	0.118***	0.318***	0.330***	0.329***	0.343***	
	(0.370)	(8.930)	(5.698)	(5.535)	(16.209)	(16.518)	(17.164)	
M2_Growth	0.224***	–0.575***	–0.349***	–0.042	–0.040	–0.029	0.031	
	(4.573)	(–10.380)	(–7.346)	(–0.982)	(–0.905)	(–0.865)	(1.053)	
Constant	0.654***	0.634***	0.633***	0.305***	0.362***	0.189***	0.351***	0.366***
	(5.632)	(11.319)	(11.095)	(4.119)	(7.122)	(2.769)	(7.300)	(9.111)
Number of obs.	28,064	25,131	25,131	28,554	26,362	28,554	28554	32075
Adjusted R2	0.654	0.507	0.506	0.502	0.502	0.503	0.502	0.459
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE								Yes

This table presents results from various robustness tests to further address endogeneity concerns. These tests include using alternative dependent (Column (1)) and independent variables (Columns (2)–(3)), clustering standard errors at the firm-year level (Column (4)), excluding the 2008–2009 financial crisis period (Column (5)), and controlling for additional macro-level variables such as Chinese economic policy uncertainty, regional economic development and marketisation levels (Column (6)). To address concerns regarding unobserved time trends in long panel data, we tried adding a linear time trend term as a control variable (Column (7)) or changing the fixed effects specification by manually introducing year dummies (Column (8)). Values in parentheses are t-values. Standard errors in Columns (1)–(3) and in (5)–(8) are clustered at the firm level, while those in Column 4 are clustered by firm and year. ***,**, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Heterogeneity analysis of climate policy uncertainty on short-term borrowing for long-term investments

Variable	(1) *SFLI*	(2) *SFLI*	(3) *SFLI*	(4) *SFLI*
L.CPU	0.031***	0.032***	0.091***	0.022***
	(9.600)	(9.453)	(2.922)	(4.885)
EnvrPat	0.011*			
	(1.904)			
EnvrPat × L.CPU	–0.004*			
	(–1.758)			
CSRReport		0.025***		
		(2.639)		
CSRReport × L.CPU		–0.007*		
		(–1.755)		
ESG_hz			0.004***	
			(3.571)	
ESG_hz × L.CPU			–0.001**	
			(–2.033)	
SCC				–0.008***
				(–2.608)
SCC × L.CPU				0.003***
				(2.653)
Size	–0.021***	–0.022***	–0.024***	–0.022***
	(–9.231)	(–9.520)	(–10.886)	(–9.688)
Age	–0.013***	–0.013***	–0.013***	–0.012***
	(–3.879)	(–3.914)	(–3.900)	(–3.580)
Leverage	0.099***	0.100***	0.115***	0.109***
	(10.304)	(10.356)	(11.798)	(10.650)
ROA	–0.010***	–0.010***	–0.010***	–0.010***
	(–48.935)	(–48.929)	(–50.206)	(–47.658)
Cashflow	–0.611***	–0.611***	–0.608***	–0.611***
	(–50.170)	(–50.119)	(–49.743)	(–49.535)
Top1	0.000***	0.000***	0.000**	0.000***
	(3.012)	(3.016)	(2.416)	(3.199)
Dual	0.003	0.003	0.004*	0.003
	(1.353)	(1.415)	(1.762)	(1.369)
Salary	–0.001***	–0.001***	–0.002***	–0.301
	(–13.074)	(–13.300)	(–18.301)	(–0.816)
Firm_Growth	–0.053***	–0.053***	–0.052***	–0.054***
	(–20.219)	(–20.112)	(–19.504)	(–19.764)
GDP_Growth	0.319***	0.318***	0.330***	0.316***
	(16.082)	(16.027)	(16.466)	(14.714)
M2_Growth	–0.039	–0.030	–0.066**	–0.055*
	(–1.431)	(–1.098)	(–2.423)	(–1.810)
Constant	0.302***	0.314***	0.108	0.356***
	(6.519)	(6.723)	(1.201)	(7.252)
Number of obs.	28532	28554	27500	26784
Adjusted R^2	0.502	0.502	0.507	0.508
Firm_FE	Yes	Yes	Yes	Yes

This table presents heterogeneity analysis examining how climate policy uncertainty (CPU) affects short-term borrowing for long-term investments (SFLI) across different dimensions of firms' climate resilience. Columns (1)–(3) capture climate resilience-enhancing characteristics: *EnvrPat* is measured as the natural logarithm of the number of green invention and utility model patent applications plus one; *CSRReport* equals 1 if the firm voluntarily discloses environmental information; and *ESG_hz* is a continuous ESG performance score from the Huazheng ESG database (higher scores indicate better performance). Column (4) assesses supply chain vulnerability. *SCC* (Supply Chain Concentration) is calculated as the average of the proportions of total assets represented by purchases from the top five suppliers and sales to the top five customers, i.e., ([Top 5 Suppliers' Purchases / Total Assets] + [Top 5 Customers' Sales / Total Assets]) / 2. Values in parentheses are t-values, clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Mechanism Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	LWLH	*KZ*	*Z_dum*	*LA*	*ASY*	*Res_DD*	*Res_Jones*	*Opacity*	*MCA_firm*
L.CPU	0.046***	1.319***	0.082***	–2.760**	0.375***	0.078***	0.007***	0.074***	–0.005***
	(11.279)	(35.625)	(11.127)	(–2.012)	(53.566)	(2.586)	(2.797)	(3.550)	(–35.410)
Size	–0.006***	–0.557***	0.045***	0.292	–0.244***	–0.002	–0.004*	–0.103***	0.002***
	(–3.188)	(–18.266)	(6.868)	(0.413)	(–32.938)	(–0.125)	(–1.788)	(–7.633)	(9.249)
Age	0.030***	0.824***	–0.073***	–0.789	–0.232***	–0.023	0.001	0.145***	0.007***
	(9.453)	(16.096)	(–7.612)	(–0.722)	(–22.144)	(–1.027)	(0.271)	(6.417)	(26.693)
Leverage	0.020**	6.688***	0.652***	–0.618	0.313***	–0.005	0.023***	0.396***	–0.003***
	(2.539)	(54.333)	(24.535)	(–0.203)	(12.930)	(–0.228)	(3.186)	(6.814)	(–4.448)
ROA	0.000*	–0.050***	–0.012***	–0.031	–0.006***	–0.002***	–0.003***	–0.015***	0.000***
	(1.956)	(–19.949)	(–24.961)	(–0.470)	(–13.282)	(–3.603)	(–15.433)	(–15.899)	(3.938)
Cashflow	–0.016**	–6.963***	–0.047***	2.479	–0.072***	0.048**	0.064***	–0.051	–0.001***
	(–2.291)	(–53.051)	(–3.202)	(0.722)	(–3.727)	(2.076)	(7.873)	(–1.154)	(–3.809)
Top1	0.000***	–0.003	0.000	–0.072	0.005***	0.001	0.000	–0.004***	0.000**
	(4.065)	(–1.539)	(0.101)	(–1.450)	(11.626)	(1.145)	(1.018)	(–4.394)	(2.441)
Dual	0.002	–0.019	0.003	–0.395	–0.002	–0.002	–0.000	0.004	0.000
	(0.788)	(–0.590)	(0.467)	(–0.431)	(–0.264)	(–0.172)	(–0.018)	(0.262)	(1.139)
Salary	0.224	–7.665	0.001***	0.004	–0.006***	3.649*	0.091	0.390	0.000**
	(0.798)	(–1.428)	(5.099)	(0.122)	(–18.999)	(1.853)	(0.367)	(0.460)	(2.149)
Firm_Growth	–0.002	–0.188***	–0.018***	–0.105	0.005	0.153***	0.034***	–0.015	–0.000
	(–1.369)	(–7.245)	(–4.380)	(–0.118)	(1.229)	(4.055)	(9.770)	(–1.507)	(–0.892)
GDP_Growth	0.124***	11.075***	0.288***	–8.782	2.082***	0.184	0.016	0.736***	0.016***
	(4.303)	(45.147)	(6.062)	(–1.068)	(43.828)	(1.202)	(1.013)	(5.701)	(16.997)
M2_Growth	0.855***	12.356***	–0.038	–21.401*	0.337***	0.550***	0.130***	1.171***	–0.027***
	(13.114)	(35.156)	(–0.539)	(–1.810)	(4.884)	(3.013)	(5.073)	(5.520)	(–18.479)
Constant	–0.287***	3.380***	–1.193***	9.885	4.297***	–0.138	0.097**	3.566***	–0.030***
	(–6.244)	(5.258)	(–8.465)	(0.640)	(27.143)	(–0.507)	(2.330)	(11.961)	(–7.358)
Number of obs.	10948	27296	28554	27274	28509	26881	27567	21433	27215
Adjusted R^2	0.147	0.751	0.523	–0.012	0.655	0.016	0.148	0.457	0.776
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents a mechanism analysis of firms' bank liquidity hoarding exposure, financing limitations, and information asymmetry as pathways via which CPU influences short-term borrowing for long-term investment (SFLI). Bank liquidity hoarding exposure is measured by (1) *LWLH* (Loan-weighted liquidity hoarding), calculated as firms' loan-weighted averages of banks' liquidity hoarding ratios, following Ma et al. (2022); higher values indicate greater exposure to bank liquidity hoarding (See Appendix D for details); (2) *KZ* index (Kaplan & Zingales,1997), indicating overall financing constraints (higher values denote tighter conditions); (3) *Z_dum*, a financial distress dummy equal to 1 if Altman's Z-score ≤ 1.8(Altman,1968); (4) *LA*, defined as the ratio of new long-term debt to fixed asset investment (Liu & Ye, 2022), with lower values indicating greater funding gaps. Information asymmetry proxies include: (5) *ASY* index **(**Bharath et al., 2009**)**, derived via principal component analysis based on liquidity, illiquidity, and return reversals (See Appendix E for details); (6–7) earnings management indicators *Res_DD* and *Res_Jones*, calculated following Dechow and Dichev (2002) and the modified Jones model (Dechow et al., 1995), with higher values indicating greater earnings manipulation; (8*) Opacity*, a disclosure quality score assigned from 1 (excellent transparency) to 4 (poor transparency), based on stock exchange ratings; (9) *MCA_firm*, constructed via textual analysis of the frequency of climate-related keywords in firms' management discussion and analysis sections, reflecting voluntary climate-related disclosure by management (Lei *et al.*,2023). Detailed definitions and construction methods are provided in Appendix B2. T-values are in parentheses, clustered at the firm level. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 7. Results of economic consequences of investment-financing maturity mismatches under climate policy uncertainty

Variable	(1) *EDF*	(2) *EDF*	(3) *ROE_risk02*	(4) *ROE_risk02*
L.CPU	0.009***	0.011***	0.011***	0.014***
	(5.905)	(5.993)	(10.256)	(11.391)
SFLI		–0.043***		–0.088***
		(–2.818)		(–6.577)
SFLI × *L.CPU*		0.016**		0.034***
		(2.521)		(5.989)
Size	0.004***	0.004***	–0.007***	–0.007***
	(3.767)	(3.732)	(–6.848)	(–6.672)
Age	–0.005***	–0.006***	0.008***	0.008***
	(–3.495)	(–3.763)	(5.385)	(4.923)
Leverage	0.019***	0.020***	0.099***	0.100***
	(6.162)	(6.198)	(19.155)	(19.184)
ROA	–0.000**	–0.000**	–0.001***	–0.001***
	(–2.301)	(–2.493)	(–14.312)	(–13.412)
Cashflow	–0.003*	–0.007**	0.005*	–0.000
	(–1.653)	(–2.202)	(1.910)	(–0.044)
Top1	–0.000	–0.000	–0.000***	–0.000***
	(–0.120)	(–0.158)	(–4.660)	(–4.743)
Dual	0.000	0.000	–0.000	–0.000
	(0.033)	(0.017)	(–0.265)	(–0.280)
Salary	–0.000***	–0.000***	–0.001***	–0.001***
	(–3.050)	(–3.017)	(–27.699)	(–26.994)
Growth	–0.002***	–0.002***	0.002***	0.001*
	(–2.632)	(–3.003)	(2.724)	(1.943)
GDP_Growth	0.019**	0.021***	0.028***	0.031***
	(2.532)	(2.697)	(3.846)	(4.191)
M2_Growth	0.067***	0.065***	0.052***	0.048***
	(4.157)	(4.088)	(4.329)	(3.972)
Constant	–0.125***	–0.128***	0.127***	0.119***
	(–4.893)	(–4.908)	(5.746)	(5.336)
Number of obs.	25,574	25,574	28,516	28,516
Adjusted R^2	0.038	0.038	0.518	0.519
Firm_FE	Yes	Yes	Yes	Yes

This table reports the impact of climate policy uncertainty (CPU) and its interaction with short-term borrowing for long-term investment (SFLI) on corporate risk. Column (1) uses expected default probability (EDF) to estimate default risk; higher values indicate a higher likelihood of default (See Appendix D for details). Column (2) uses the standard deviation of industry-adjusted ROE (*ROE_risk02*) to measure operational risk; higher values indicate higher volatility. Values in parentheses are t-statistics with standard errors clustered at the firm level. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Appendix A. Variable definition

Table A1. Main variables and definitions

Variable type	Variable name	Variable definition
Dependent variable	*SFLI*	[Capital expenditures on fixed assets and other investments - (current period increase in long-term borrowings + current period increases in equity + net cash flow from operating activities + cash inflows from the sale of fixed assets)] / total assets
	SFLI_dum	Indicator that equals one if SFLI is greater than 0, and zero otherwise.
	DebtCL_Asset	Current liabilities scaled by total assets
	DebtNCL_Asset	Non-current liabilities scaled by total assets
Independent variable	*CPU*	Chinese climate policy uncertainty index by Ma et al. (2023). See Appendix C for details.
Control variables	*Size*	Natural logarithm of 1 plus the book value of the total assets
	Leverage	The ratio of total debt to total assets
	Age	Natural logarithm of 1 plus the age of the company
	Cashflow	Operating cash flow scaled by total assets
	ROA	Net income scaled by total assets at the end of the year.
	Firm_Growth	Revenue growth rate
	Top1	Percentage of shares held by the largest shareholder
	Dual	Indicator that equals one if the Chairman and CEO are the same person, and zero otherwise
	Salary	Ratio of compensation of top three executives to revenue
	GDP_Growth	(Real GDP_t - Real GDP_{t-1}) / Real GDP_{t-1}, where t indicates the current period and t–1 indicates the previous
	M2_Growth	(Money $Supply_t$ - Money $Supply_{t-1}$) / Money $Supply_{t-1}$, where t represents the current period and t–1 indicates the previous

This table defines the dependent, independent, and control variables used in this study. Firms' financial data were collected from the China Stock Market & Accounting Research (CSMAR) database. The climate policy uncertainty index was retrieved from Ma *et al*. (2023). GDP growth was calculated using data from the annual *China Statistical Yearbook*, and M2 growth data were sourced from the People's Bank of China website (http://www.pbc.gov.cn/).

Table A2. Mechanism variables and construction details

Variable	Description & Construction	Source

LWLH	Loan-weighted liquidity hoarding exposure, calculated as firms' loan-weighted average of banks' liquidity hoarding ratios. Higher values indicate firm's exposure to bank liquidity hoarding.	Author calculation based on Ma *et al.* (2022)
KZ	Kaplan–Zingales index, measuring corporate financing constraints. A higher value indicates tighter constraints.	CSMAR
Z_dum	Dummy variable based on Altman's Z-score. Z = 100×(0.012×WC/TA+0.014×RE/TA+0.033×EBIT/TA+0.006×MVE/Liabilities+0.999 × Sales/TA). Equals 1 if Z ≤ 1.8, indicating financial distress.	Altman (1968)
LA	Ratio of new long-term debt to new fixed asset investment. Higher values imply better long-term funding adequacy.	Author calculation following Liu & Ye (2022)
ASY	First principal component extracted from daily liquidity, illiquidity, and return reversal measures, capturing trading-based information asymmetry.	Bharath *et al.*, (2009)
Res_DD	Residual from earnings management estimation using the Dechow and Dichev (2002) model. Higher values indicate poorer earnings quality.	Dechow & Dichev (2002)
Res_Jones	Residual from earnings management estimation using the modified Jones model (Dechow et al., 1995). Higher values indicate poorer earnings quality.	Dechow *et al.*, (1995)
Opacity	Corporate information transparency score published by stock exchanges. Categories A (1) to D (4), with higher scores indicating lower transparency.	CSMAR
MCA_firm	The climate disclosure intensity indicator is constructed through textual analysis of the Management Discussion and Analysis (MD&A) section in firms' annual reports, measuring the frequency of climate-related keywords to quantify managerial attention and disclosure on climate issues.	Lei *et al.* (2023)

Appendix B. Comparison of control variables before and after entropy balance matching

We select firm-level control variables as covariates for entropy balancing based on two main considerations.

First, these variables are closely related to corporate decisions regarding investment-financing maturity structure and have been extensively validated in the literature (Fan *et al.*, 2012; Custódio *et al.*, 2013; Wang *et al.*, 2021a). Specifically, firm fundamentals – including firm size (*Size*), age (*Age*), leverage (*Leverage*), and return on assets (*ROA*) – affect financing capacity and maturity preferences. Corporate governance indicators, such as ownership concentration (*Top1*), CEO duality (*Dual*), and executive compensation (*Salary*), reflect agency costs and managerial prudence, thereby influencing maturity structure decisions. Additionally, cash flow characteristics, including operating cash flow (*Cashflow*) and revenue growth (*Firm_Growth*), shape both short-term repayment pressure and long-term investment demand. Collectively, these covariates provide strong explanatory power for firms' maturity structure behaviour and exhibit substantial internal coherence.

Second, in the context of matching methods, the balance of covariates between the treatment and control groups directly affects comparability and the robustness of estimated treatment effects. Entropy balancing aims to achieve identical distributions of covariates (in terms of mean, variance, and skewness) across groups through reweighting. Therefore, the selected covariates must be theoretically relevant and empirically suitable for achieving distributional balance. The combination of these firm-level variables ensures both conceptual soundness and empirical feasibility, thereby enhancing match quality and identification credibility. The matching results are presented below.

Table B1. Comparison of control variables before and after entropy balance matching

Panel A: Before matching	Treated group			Control group		
Variable	Mean	Variance	Skewness	Mean	Variance	Skewness
Size	21.75	1.264	0.662	22.35	1.823	0.775
Age	2.109	0.6027	–0.379	2.242	0.522	–0.491
Leverage	0.459	0.049	0.248	0.438	0.042	0.188
ROA	–1.219	73.62	–1.673	5.085	23.06	0.292
Cashflow	0.037	0.006	–0.060	0.02	0.006	0.926
Top1	32.68	202.6	0.542	34.69	225.9	0.482
Dual	0.297	0.209	0.888	0.253	0.189	1.137
Salary	0.012	0.795	95.2	0.0017	0.001	150.8
Growth	0.075	0.152	2.862	0.211	0.213	3.631

Panel B: After matching	Treated group			Control group		
Variable	Mean	Variance	Skewness	Mean	Variance	Skewness
Size	21.75	1.264	0.662	21.75	1.83	0.696
Age	2.109	0.603	–0.379	2.11	0.570	–0.351
Leverage	0.459	0.049	0.248	0.459	0.064	0.438
ROA	–1.219	73.62	–1.673	–1.212	114.1	–1.551
Cashflow	0.037	0.006	–0.060	–0.037	0.009	–0.681
Top1	32.68	202.6	0.542	32.69	206.8	0.589
Dual	0.297	0.209	0.888	0.297	0.209	0.888
Salary	0.012	0.795	95.2	0.012	0.023	22.35
Growth	0.075	0.152	2.862	0.076	0.177	2.491

Appendix C. Construction of the Chinese Climate Policy Uncertainty Index (CPU)

The national-level Chinese Climate Policy Uncertainty (CPU) index used in this study is adapted from the study by Ma et al. (2023), who employed the MacBERT deep learning model to analyse 1.76 million news articles from six authoritative national newspapers (*People's Daily*, *Guangming Daily*, *Economic Daily*, *Global Times*, *Science and Technology Daily*, and *China News Service*) spanning 2000–2022. This text-based method offers robust technical advantages for measuring policy uncertainty by leveraging pre-trained language models to automatically extract contextual semantics such as policy ambiguity and implementation risks, which mitigates the subjective biases inherent in traditional keyword-based approaches. The index construction incorporates rigorous cross-validation and inter-source standardisation, ensuring high accuracy (97.8%) and reliability for analysis. For our research, this serves as a credible and objective proxy for national-level climate policy uncertainty.

The data is available at from https://doi.org/10.6084/m9.figshare.24071250.v3

Appendix D. Construction of loan-weighted liquidity hoarding (LWLH)

Following Ma et al. (2022), we define loan-weighted liquidity hoarding (LWLH) as a measure of firms' exposure to banks' liquidity hoarding behaviour at the firm level. This measure assesses the extent to which a firm is impacted by liquidity shocks resulting from banks' liquidity management practices, which directly influence lending capacities and terms, particularly during periods of CPU. The three-step construction of the LWLH measure is as follows:

First, we calculate bank-level liquidity hoarding (*LHBank*) based on banks' balance sheet items categorised into liquid and illiquid assets and liabilities. Specifically, liquidity hoarding is calculated as:

LWLH=+(1/2)×liquidity assets +(–1/2)× illiquid assets +(+1/2)×liquidity liabilities

Items are assigned liquidity weights of +1/2 or –1/2 based on their contribution to liquidity, with liquid assets and liabilities enhancing liquidity, and illiquid assets reducing it. Illiquid liabilities are excluded due to their limited relevance to liquidity hoarding. The classification of balance sheet items into these categories is presented in Table D1.

Second, we normalise this measure by dividing *LHBank* by the total assets of the banks, obtaining the standardised measure *LHBank_TA*, which makes it comparable across banks of different sizes. This normalization ensures that our measure accurately reflects the intensity of banks' liquidity hoarding, regardless of bank size.

Third, these bank-level liquidity hoarding measures are aggregated to the firm level, leveraging firm-bank lending relation data. Specifically, for each firm, we calculate a loan-weighted measure of exposure *(LWLH*), which is defined as the weighted average of each associated bank's liquidity hoarding measure (*LHBank_TA),* weighted by the firm's proportion of loans from each bank. The formula is as follows:

$$LWLH_{i,t} = \sum_{j=1}^{N} \left(LW_{i,j} * \ LHBank\_TA\ _{j,t} \right)$$

where $LWLH_{i,t}$ represents the proportion of loans firm iii obtains from bank j, and $LHBank\_TA\ _{j,t}$ is bank j's normalised liquidity hoarding measure at time t. Consequently, firms borrowing primarily from banks with high liquidity hoarding will face greater liquidity risks, thereby influencing their financing maturity choices and investment decisions, particularly during periods of increased CPU.

Data Note: The construction of *LWLH* relies on firm-bank loan data from CSMAR, which are systematically available from 2012 onwards. The mechanism analysis using *LWLH* covers the period from 2012 to 2022, whereas the main analysis spans the period from 2007 to 2022. Bank-level data are obtained from Wind and CSMAR, covering major state-owned banks, joint-stock commercial banks, and selected city and rural commercial banks. After excluding policy banks and unmatched firm-bank relations, the resulting sample for the LWLH-based analysis is smaller than the baseline. Nevertheless, it remains sufficiently representative and reflects the most comprehensive data coverage achievable for this variable.

Table D1. Classification and weight allocation of bank's balance sheet activities

Assets		*Liabilities*
Liquid assets (weight: + 1/2)	*Illiquid assets* (weight: –1/2)	(weight: + 1/2)
Cash and deposits with the central bank	Loans and advances	Deposits from other financial institutions
Deposits with other financial institutions	Financial assets available for sale	Borrowings from the central bank
Precious metals	Held-to-maturity investments	Funds borrowed from other banks
Funds lent to other banks	Long-term equity investments	Demand deposits
Trading financial assets	Accounts receivable investments	Short-term borrowings
Financial assets purchased under resale agreements	Fixed assets	Trading financial liabilities
Derivative financial assets	Construction in progress	Derivative financial liabilities
Other receivables	Intangible assets	Financial assets sold under repurchase agreements
Interest receivables	Goodwill	Employee compensation payable
Dividend receivables	Long-term deferred expenses	Taxes payable
	Deferred tax assets	Interest payable
	Investment properties	Dividends payable
	Other assets	Deferred income
		Other payables

Appendix E. Construction of Kaplan & Zingales (KZ) index

Following Kaplan & Zingales (1997), we constructed a KZ index as a proxy the degree of financial constraints for Chinese listed firms. The construction involves the following steps:

(1) Classification of Financial Indicators

For each firm-year observation, we classify the following variables based on whether their values are above or below the sample median:

- Operating cash flow to lagged total assets: $CF_{i,t}/A_{i,t-1}$
- Dividend payments to lagged total assets: $DIV_{i,t}/A_{i,t-1}$
- Cash holdings to lagged total assets: $C_{i,t}/A_{i,t-1}$
- Leverage ratio: $LEV_{i,t}$

- Tobin's Q: $Q_{i,t}$

The indicator assignment is as follows (assign 1 if condition is met, otherwise 0):

- If $CF_{i,t}/A_{i,t-1}$ < median, KZ1 = 1
- If $DIV_{i,t}/A_{i,t-1}$ < median, KZ2 = 1
- If $C_{i,t}/A_{i,t-1}$ < median, KZ3 = 1
- If $LEV_{i,t}$ > median, KZ4 = 1
- If $Q_{i,t}$ > median, KZ5 = 1

(2) Initial KZ Index Calculation

The unweighted KZ index is the sum of these binary indicators:

$$KZ = KZ1 + KZ2 + KZ3 + KZ4 + KZ5$$

(3) Ordered Logistic Regression

Next, we perform an ordered logit regression using the unweighted KZ index (from step 2) as the dependent variable, and the five continuous financial ratios:

$$KZ_{it} = \alpha_1 \frac{CF_{it}}{ASSET_{it-1}} + \alpha_2 LEV_{it} + \alpha_3 \frac{DIV_{it}}{ASSET_{it-1}} + \alpha_4 \frac{CASH_{it}}{ASSET_{it-1}} + \alpha_5 Q_{i,t}$$

Using the estimated results from the ordered logit model described above, we compute the KZ index for each listed firm in each year. A higher KZ index indicates a higher degree of financial constraint faced by the firm.

Appendix F. Variables used to construct the information asymmetry index (ASY)

The ASY index captures the 'lemon premium' required by informed traders to compensate for adverse selection, as higher information asymmetry increases such premiums and reduces stock liquidity. It is constructed using daily trading data, incorporating liquidity ratios, illiquidity measures, and return reversal indicators. The first principal component extracted from these three variables serves as a composite proxy for information asymmetry.

1. Liquidity ratio (LR):

$$LR_{it} = -\frac{1}{D_{it}} \sum_{k=1}^{D_{it}} \sqrt{\frac{V_{it}(k)}{|r_{it}(k)|}};$$

2. Illiquidity ratio (ILR):

$$ILR_{it} = \frac{1}{D_{it}} \sum_{k=1}^{D_{it}} \sqrt{\frac{|r_{it}(k)|}{V_{it}(k)}},$$

where $r_{it}(k)$ represents the stock return of firm i on the k trading day of year t, $V_{it}(k)$ is the trading volume on that day, and D_{it} indicates the total number of trading days in the respective year.

3. Return reversal index (GAM):

$$GAM_{it} = |\gamma_{it}|$$

$$r_{it}^{e}(k) = \theta_{it} + \varphi_{it} r_{it}(k-1) + \gamma_{it} V_{it}(k-1)\text{sign}\,[r_{it}^{e}(k-1)] + \varepsilon_{it}(k)$$

In this context, $r_{it}^{e}(k) = r_{it}(k) - r_{mt}(k)$ denotes the excess return, where $r_{mt}(k)$ denotes the market return weighted by market capitalisation. θ_{it} is the intercept term, V_{it} represents the trading volume, and $\varepsilon_{it}(k)$ is the random disturbance term.

Holding other factors constant, a higher degree of information asymmetry is associated with lower stock liquidity and larger LR, ILR, and GAM indicator values.

Appendix G. Expected default probability (EDF)

First, the Moody's KMV model derived from the Black–Scholes–Merton option pricing formula can be represented as follows:

$$\begin{cases} E = V_a N(d_1) - De^{-r_f^t} N(d_2) \\ \sigma_E = \dfrac{V_a N(d_1)}{E} \sigma_a \end{cases}$$

$$d_1 = \frac{ln\left(\frac{V_a}{D}\right) + \left(r_f + 0.5\sigma_a^2\right)t}{\sigma_a\sqrt{t}}$$

$$d_2 = d_1 - \sigma_a\sqrt{t}$$

In this model, it is necessary to determine parameters such as the risk-free rate r_f, the enterprise's debt term T, daily stock return rate r_t, the value of equity E, the volatility of the equity value σ_E, and the enterprise's default point (DP, Default Point) before solving the model iteratively. This process estimates the market value V_a of the enterprise's assets and their volatility σ_a. Then, using the formula below, we calculate the default distance (DD) and the expected default frequency (EDF):

$$DD = \frac{V_a - DP}{V_a \sigma_a},$$

$$EDF = Normal(-DD),$$

where DD represents the number of standard deviations by which the value of the enterprise's assets deviates from the default threshold. A greater default distance indicates a lower probability of default, and vice versa. EDF represents the theoretical probability that the value of the enterprise's assets will fall below the default point. The risk-free interest rate serves as the benchmark interest rate for one-year RMB deposits that year, with a debt term of $T = 1$ year. The stock yield is calculated using $r_t = ln\,(p_t/p_{t-1})$, in which $t = 1, 2, \ldots, 252$. The volatility of the equity value σ_E is generally substituted with the annual stock volatility σ_y, calculated by first determining the daily volatility of stock returns σ_d from closing stock prices, then calculating $\sigma_y = \sqrt{252}\sigma_d$ to obtain the equity value volatility σ_E. The enterprise's equity value $E =$

(outstanding shares × average annual price + number of restricted shares × net assets per share);
Default Point *DP = (1/2 × long-term liabilities + short-term liabilities)*.