Climate policy uncertainty and enterprise labor outsourcing

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Abstract

This paper investigates the impact of climate policy uncertainty on labor outsourcing among Chinese-listed companies from 2012 to 2022. We find that increased climate policy uncertainty prompts firms to choose labor outsourcing. The results hold even after several robustness tests and controlling for endogeneity. Moreover, our cross-sectional analyses indicate that the main effect is more pronounced in non-state-owned enterprises and firms without government employment stability subsidies.

Keywords: Climate policy uncertainty, Labor outsourcing, Nature of property rights, Government subsidy
JEL: G18; J20; M51

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1. Introduction

The previous literature widely recognizes that climate risk has significantly impacted human life and posed an unparalleled challenge to the global economy. Against this backdrop, the government has implemented a series of policies to respond to climate change. However, frequent climate policy adjustments may induces higher climate policy uncertainty (CPU) (Gavriilidis, 2021). Increased CPU makes it difficult for managers to predict the future influence of climate policy on companies. It is crucial, therefore, to examine whether and how such uncertainty affects actions in corporate strategic decisions (Huang, 2023; Su et al., 2024).

Since the introduction of CPU index provided by Gavriilidis (2021), a growing body of research has focused on the influence of CPU on various economic outcomes. For instance, Hoang (2022) suggests, based on real option theory, that heavy emitter firms tend to cut back on research and development (R&D) investment in response to CPU. Further research by Huang and Sun (2023) find that increased uncertainty from frequent adjustments to climate policy can induce firms to reduce investment until the uncertainty is resolved. Naturally, our study posit that CPU could be related to labor outsourcing, which is a typical labor investment decision.

Following Holcomb and Hitt (2007), outsourcing is defined as the organizing arrangement whereby firms rely on intermediate markets to provide specialized capabilities that supplement their existing capabilities along the firms' value chain. This arrangement serves as a strategic response to mitigates cost disadvantage and potential uncertainty (Choi et al., 2021; Holcomb and Hitt, 2007). Specially, labor outsourcing can increase workforce flexibility and reduce labor costs by adopting temporary labor contracts. In the past decade, the number of firms engaging in labor outsourcing activities in high-carbon industries has significantly increased from 41 (7.24%) in 2012 to 292 (29.61%) in 2022. In addition, the ratio of outsourced labor compensation to total employee compensation has risen from 0.76% in 2012 to 6.66% in 2022, representing an increase of nearly tenfold. Against this backdrop, we have strong motivation to explore why firms choose to outsource labor.

This paper assumes that CPU can compel firms to strategically outsource labor to some extent in at least two ways. We first propose based on financial friction theory that uncertainty related to climate policy will generate more

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asymmetric information between outside investors and firms in high-carbon industries, inducing adverse selection among investors (Hoang, 2022). In this context, investors may require additional risk compensation, contributing to an increased cost of capital (Ren et al., 2022). This may force firms to seek cost strategies to cope with "bad" times. Relative to long-term employment, labor outsourcing may allow firms to avoid higher litigation costs and expenditures related to employee management responsibilities. Unlike full-time employees, outsourcing allows firms to benefit from labor temporarily without a formal labor contract. In other words, labor outsourcing enables firms to transfer future expenditure responsibilities and potential production risks to third-party organizations (Holcomb and Hitt, 2007). Second, the real option theory emphasizes that investment cannot be reversed due to the incurred adjustment costs associated with uncertainty (Huang and Sun, 2023). Specifically, labor outsourcing can be considered a real option that can be purchased at the contract price for firms. Firms can freely choose to stop or continue such outsourcing activities depending on current conditions. The outsourcing contract provides a possibility for firms to adopt more prudent business strategies when facing uncertainties in the external environment. Hence, labor outsourcing is considered to be a flexible strategy to temporarily offset these detrimental effects until such uncertainty is addressed (Choi et al., 2021). Overall, labor outsourcing enables high-carbon enterprises to benefit from decreased labor costs and increased labor flexibility. These potential benefits incentivize high-carbon firms to engage in labor outsourcing during times of heightened climate policy uncertainty.

Using data of Chinese listed companies for the sample period 2012-2022, our results reveal a positive relationship between CPU and labor outsourcing. Specifically, increased CPU prompts both the occurrence and scale of corporate labor outsourcing. These results remain valid after adopting alternative samples and using an instrumental variable approach.

We contribute to the existing literature in two ways. First, we extend research on the economic consequences of CPU. Previous studies have shown that CPU affects various firm outcomes, including green innovation (Huang and Sun, 2023), asset prices (Iqbal et al., 2024), and carbon emissions (Gavriilidis, 2021). However, these studies neglect the influence of CPU on labor employment decisions. This paper adds to this line of literature by demonstrating that CPU positively affect corporate labor outsourcing. Second, we adds to the studies on the determinants of labor outsourcing. While prior research has addressed social security contributions (Pang and Zhou, 2024), financial constraints (Choi et al., 2021), and import competition (Chakraborty et al., 2024), we highlight how CPU drives labor outsourcing in high-carbon industries, drawing on financial frictions and waiting-option theories. These findings offer potential insights for policymakers and enterprises.

2. Data and methodology

The sample for this study consists of listed companies in high carbon emission industries on China's A-share market that were more affected by climate policy from 2012 to 2022.[1] Data on labor outsourcing are collected from the annual reports of listed companies. All financial data are extracted from the China Securities Market and Accounting Research (CSMAR) database, while macroeconomic variables are obtained from the National Bureau of Statistics of China. After winsorizing all continuous measures at the 1% and 99% levels and excluding firms with missing financial data, our final sample consists of 7,993 firm-year observations.[2]

We obtain the annual data on CPU index developed by Ma et al. (2023). This index leverages 1,755,826 articles from six mainstream Chinese newspapers, namely People's Daily, Guangming Daily, Economic Daily, Global Times, Science and Technology Daily, and China News Service. A higher value of this index indicates greater climate policy uncertainty.

Following Pang and Zhou (2024), we employ two proxies to capture labor outsourcing. First, we use a binary indicator (*Dumblabor*) to denote whether a firm engaged in labor outsourcing in a given year. Second, we use the ratio of outsourced labor compensation to total employee compensation (*Laborsalary*) to measure the intensity of the company's labor outsourcing activities.

[1]Since 2012, Chinese listed firms have been required to disclose information on labor outsourcing in annual reports. The definition of high carbon emission industries see Appendix A.1.

[2]The regression sample will be reduced by one period compared to the total sample. The rationale is that this paper uses corporate labor outsourcing in the following year to regress against climate policy uncertainty in order to mitigate potential endogeneity issues.

We employ two complementary baseline models to investigate the relationship between climate policy uncertainty and labor outsourcing:

$$Dumlabor_{i,t+1} = \beta_0 + \beta_1 CPU_t + \beta_2 Controls_{i,t} + \mu_p + \sigma_c + \varepsilon_{i,t} \tag{1}$$

$$Laborsalary_{i,t+1} = \begin{cases} \beta_0 + \beta_1 CPU_t + \beta_2 Controls_{i,t} + \mu_p + \sigma_c + \varepsilon_{i,t}, & \text{if } LaborOuts_{i,t} > 0 \\ 0, & \text{if } Laborsalary_{i,t} = 0 \end{cases} \tag{2}$$

where i and t denote firm and year, respectively. The vector $Controls_{i,t}$ includes all other factors affecting labor outsourcing, as described in Table B.1. μ_p and σ_c represent province and industry fixed effects, respectively. No controls for year fixed effects are used because CPU Index is the same for most firms in a given year. We used probit models to estimate Eq. (1), where the dependent variable *Dumlabor* is binary, allowing us to examine the discrete choice of whether a firm outsources labor. We then estimate Eq. (2) using tobit models because our dependent variable, *Laborsalary*, is continuous but left-censored at zero, with many firms reporting zero outsourcing expenditure. The tobit model allows us to simultaneously analyze both the decision to engage in labor outsourcing and its intensity, thereby avoiding potential estimation bias that could arise from ordinary least squares regression when handling censored dependent variables. Robust standard errors are clustered at the firm level. The descriptive statistics and correlation matrix for our main variables are presented in Tables Table B.2 and Table B.4, respectively.

3. Empirical results

3.1. Baseline regression results

Table 1 gives resulting estimates for Eq. (1) and (2). Columns (1) and (2) exclude control variables, while columns (3) and (4) include them. The CPU coefficients are consistently positive and statistically significant at least at the 5% level, indicating that increased CPU compels corporate labor outsourcing.

Table 1
Baseline regression results.

	Probit	Tobit	Probit	Tobit
	(1)	(2)	(3)	(4)
Variables	$Dumblabor_{t+1}$	$Laborsalary_{t+1}$	$Dumblabor_{t+1}$	$Laborsalary_{t+1}$
CPU	0.502^{***}	0.190^{***}	0.225^{**}	0.106^{***}
	(0.046)	(0.020)	(0.099)	(0.037)
Controls	NO	NO	YES	YES
Province FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
N	6734	6734	6734	6734
Pseudo R^2	0.065	0.073	0.097	0.109

Notes: This table presents OLS regression estimates for the effect of CPU on labor outsourcing. Columns (1) and (3) report the OLS regression estimates of Eq. (1), while columns (2) and (4) report those of Eq. (2). Province FE and Industry FE represent province and industry fixed effects, respectively. Standard errors are clustered at the firm level and reported in parentheses. *,**, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

3.2. Robustness checks

3.2.1. Alternative sample period

During the COVID-19 pandemic, the global spread of the virus prompted the Chinese government to implement a series of strict control measures, including business shutdowns and restrictions on population mobility, to limit the virus's spread. These interventions disrupted labor mobility and created market supply-demand imbalances (Dai et al., 2021), potentially altering the relationship between CPU and labor outsourcing. To mitigate this effect, we limited our sample by excluding data from 2020-2022 and re-examined equations (1) and (2). The results in columns (1) and (2) of Table B.3 again support our conclusions.

3.2.2. *Two-stage least squares method*

Endogeneity issues may present and disturb the baseline regression due to potential environmental changes influencing climate policy formulation. Following Mo and Liu (2023), the U.S. climate policy uncertainty index developed by Gavriilidis (2021) is used as an instrumental variable in a two-stage least squares estimation. As climate change risk is a global issue, the U.S., as the world's largest economy, frequently adjusts its climate policies, which may influence China's climate policy formulation. However, these adjustments are unlikely to be directly related to the labor outsourcing decisions of Chinese firms. Columns (3) and (5) in Table B.3 demonstrate that the U.S. climate policy uncertainty index is effective, and the coefficient of CPU is significantly positive in columns (4) and (6), consistent with the main regression results.

3.3. *Cross-sectional analyses*

State-owned enterprises (SOEs) can better withstand the negative consequences of increased CPU due to implicit government guarantees and financial support (Borisova and Megginson, 2011). Therefore, non-state-owned enterprises (Non-SOEs) are more likely to adopt labor outsourcing strategies in response to increased CPU compared to SOEs. Columns (1) and (2) of Table 2 show a significantly negative coefficient for the interaction term $SOEs * CPU$, confirming this analysis.

In addition, we examine how government subsidy related to employment shapes the relation between CPU and labor outsourcing. The presence of employment stabilization subsidies ($Subsidy$) lowers corporate labor costs. Furthermore, these subsidies function to certify the value of firms, enabling high-carbon companies to better respond to uncertainty. Hence, firms with greater subsidy have more ability to withstand such uncertainty, this, in turn presents lower labor outsourcing. These results are shown in column (3) and (4) of Table 2.

Table 2
Cross-sectional analyses results.

	Nature of property rights		Employment stabilization subsidies	
	Probit	Tobit	Probit	Tobit
	(1)	(2)	(3)	(4)
Variables	$Dumblabor_{t+1}$	$Laborsalary_{t+1}$	$Dumblabor_{t+1}$	$Laborsalary_{t+1}$
SOEs∗CPU	-0.278***	-0.074**		
	(0.100)	(0.037)		
SOEs	0.317***	0.095**		
	(0.113)	(0.041)		
Subsidy∗CPU			-2.579***	-0.825***
			(0.438)	(0.206)
Subsidy			0.334	0.172**
			(0.248)	(0.076)
CPU	0.381***	0.148***	2.791***	0.928***
	(0.109)	(0.041)	(0.450)	(0.211)
Controls	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
N	6734	6734	6734	6734
Pseudo R^2	0.103	0.113	0.098	0.110

Notes: This table reports the results of the cross-sectional analyses for the nature of property and employment stabilization subsidies. In columns (1) and (2), the coefficients on the interaction terms, $SOEs * CPU$, are significantly negative, indicating that the effect of CPU on labor outsourcing is more pronounced for Non-SOEs. In columns (3) and (4), the coefficients on the interaction terms, $Subsidy * CPU$, are significantly negative, suggesting that the effect of CPU on labor outsourcing is more pronounced for firms without employment stabilization subsidies. Province FE and Industry FE indicate the control of fixed effects for province and industry, respectively. Standard errors are clustered at the firm level and reported in parentheses. *,**, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

4. Conclusions

This paper investigates the impact of CPU on firms' labor outsourcing behavior using panel data from 2012 to 2022 on Chinese listed firms operating in high-carbon industries. We find that CPU increases firms' propensity for labor outsourcing, and this finding remains robust after excluding the influence of the COVID-19 pandemic and employing an instrumental variable approach. Cross-sectional evidence underscores the fact that NSOEs and firms without government subsidies are more likely to be affected by CPU and adopt labor outsourcing strategy.

Our findings reveal several important insights. First, this study establishes a new link between CPU and labor employment decisions in Chinese high-carbon industries. The findings suggest that increased CPU forces firms to outsource labor. This is because the rise in climate exposure enables the government to frequently adjust climate policy, which disturbs market expectations. Hence, we suggest that the government implement a moderate climate policy to mitigate the adverse effects of CPU on the labor market. Second, the government should pay more attention to non-state-owned enterprises that are likely vulnerable to uncertainty when implementing climate policy. Moreover, the government can provide moderate employment stabilization subsidies to maintain the stability of the labor market.

Declaration of interests

We have nothing to declare.

Acknowledgments

We thank Editor Max Croce for his fair and thoughtful guidance throughout the review process. The valuable comments and suggestions from the anonymous reviewer significantly enhanced thispaper's quality. All remaining errors are our own.

Appendix A. High-carbon industries list

Following Wang et al. (2024), carbon-intensive industries include electricity, heat, and gas production and supply; oil and gas extraction, non-metallic and non-ferrous metal mining; non-ferrous metal and ferrous metal smelting and rolling processing; chemical raw material, chemical fiber and chemical product manufacturing; metal, ferrous metal, and non-metallic mineral products; petroleum processing and coking; nuclear fuel processing; construction and decoration; housing; civil engineering; wood processing; paper making; wood, bamboo, rattan, palm, grass and paper products; metal products; machinery and equipment repair.

Appendix B. Additional Tables

Table B.1
Variables definition

Symbol	Measurement
Dumblabor	A dummy variable equal to 1 if the firm engages in labor outsourcing, and 0 otherwise.
Laborsalary	The fraction of outsourcing remuneration expenses to the total corporate employee compensation.
CPU	The climate policy uncertainty index of China. See https://figshare.com/articles/dataset/China_s_CPU_index/24071193/1 for more information.
Age	The natural logarithm of the number of years a firm has been listed.
Size	The natural logarithm of total assets.
ROA	The net income divided by total assets.
Lev	The liabilities to total assets.
Cash	The ratio of the sum of cash and trading financial assets to total assets.
Board	The natural logarithm of the number of board directors.
Indep	The number of independent directors divided by the total number of directors.
Top1	The percentage of largest shareholder shares to the total number of outstanding shares.
EmployeeNum	The natural logarithm of the number of employees.
Salary	The natural logarithm of employee compensation.
EPU	The Economic Policy Uncertainty Index, is calculated by averaging the values over the preceding period, with the result then divided by 100. See https://www.policyuncertainty.com/china_epu.html for more information.
GDPgrowth	GDP growth rate.
Mobility	Net Permanent Population Migration Rate = (Total Population - Registered Population) / Total Population.
Minwage	The minimum wage in the city where the firm operates/1000.
Averwage	The average wage in the city where the firm operates/1000.

Table B.2
Descriptive statistics.

Variable	N	Mean	SD	Min	Max
Dumblabor	7,993	0.202	0.401	0.000	1.000
Laborsalary	7,993	0.042	0.137	0.000	0.774
CPU	7,993	2.553	0.349	2.125	3.200
Age	7,993	2.310	0.786	0.000	3.401
Size	7,993	22.466	1.412	19.655	26.210
ROA	7,993	0.660	0.415	0.058	2.470
Lev	7,993	0.461	0.214	0.054	0.944
Cash	7,993	0.163	0.124	0.015	0.722
Board	7,993	1.560	1.046	0.000	2.639
Indep	7,993	0.260	0.178	0.000	0.571
Top1	7,993	35.010	14.748	8.540	74.295
EmployeeNum	7,993	7.650	1.358	2.639	11.079
Salary	7,993	17.238	1.581	12.210	21.439
EPU	7,993	4.573	2.352	1.139	7.919
GDPgrowth	7,993	6.734	2.614	-0.200	12.600
Mobility	7,993	0.115	0.195	-0.166	0.874
Minwage	7,993	1.765	0.350	1.050	2.590
Averwage	7,993	8.585	3.458	3.897	21.248

Notes: This table report the descriptive statistics for the sample firms. The sample consists of 7,993 firm-year observations over an 11-year period from 2012 to 2012. All variables are winsorized at 1% and 99%.

Table B.3
Robustness checks results.

	Alternative sample period		Two-stage least squares method			
	Probit	Tobit	First stage	Two stage	First stage	Two stage
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	$Dumblabor_{t+1}$	$Laborsalary_{t+1}$	CPU	$Dumblabor_{t+1}$	CPU	$Laborsalary_{t+1}$
CPU	0.363**	0.160**		0.979***		0.417***
	(0.160)	(0.062)		(0.297)		(0.111)
iv_CPU			0.362***		0.361***	
			(0.012)		(0.010)	
Controls	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Kleibergen-Paap F statistic			10.98**		14.18***	
N	5007	5007	6734	6734	6734	6,734
Pseudo R^2	0.113	0.130	0.756		0.756	

Notes: This table reports the results of robustness checks. Columns (1) and (2) show regression results for an alternative sample period (2012-2019). Column (3) - (6) show the regression results of using instrument variable, iv_CPU. Columns (3) and (4) employ probit models, while columns (5) and (6) use tobit models. All variables are defined in detail in Table B.1. *,**, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Table B.4

Correlation table.

	CPU	Age	Size	ROA	Lev	Cash	Board	Indep	Top1	EmployeeNum	Salary	EPU	GDPgrowth	Population	Minwage	AverWage
CPU	1.000															
Age	0.007	1.000														
	(0.531)															
Size	0.032***	0.404***	1.000													
	(0.004)	(0.000)														
ROA	0.013	0.011	0.024**	1.000												
	(0.256)	(0.319)	(0.033)													
Lev	-0.051***	0.338***	0.501***	0.007	1.000											
	(0.000)	(0.000)	(0.000)	(0.542)												
Cash	0.014	-0.277***	-0.273***	0.018	-0.407***	1.000										
	(0.205)	(0.000)	(0.000)	(0.106)	(0.000)											
Board	-0.011	0.080***	0.213***	0.036***	0.069***	-0.082***	1.000									
	(0.326)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)										
Indep	-0.003	0.068***	0.186***	0.037***	0.058***	-0.071***	0.940***	1.000								
	(0.765)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)									
Top1	-0.039***	-0.053***	0.273***	0.106***	0.108***	-0.016	-0.037***	-0.027**	1.000							
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.159)	(0.001)	(0.014)								
EmployeeNum	0.023**	0.320***	0.770***	0.173***	0.402***	-0.269***	0.215***	0.193***	0.246***	1.000						
	(0.044)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)							
Salary	0.076***	0.284***	0.732***	0.144***	0.310***	-0.158***	0.202***	0.195***	0.218***	0.702***	1.000					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
EPU	0.169***	0.014	0.082***	0.003	-0.094***	0.163***	-0.065***	-0.049***	-0.071***	-0.069***	0.164***	1.000				
	(0.000)	(0.211)	(0.000)	(0.787)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
GDPgrowth	0.251***	-0.028**	-0.096***	0.035***	0.049***	-0.120***	0.036***	0.024**	0.039***	0.064***	-0.106***	-0.700***	1.000			
	(0.000)	(0.013)	(0.000)	(0.002)	(0.000)	(0.000)	(0.001)	(0.030)	(0.001)	(0.000)	(0.000)	(0.000)				
Population	0.015	-0.021*	0.104***	-0.051***	0.064***	-0.017	0.033***	0.042***	0.054***	0.012	0.064***	0.028**	-0.112***	1.000		
	(0.181)	(0.056)	(0.000)	(0.000)	(0.000)	(0.138)	(0.003)	(0.000)	(0.000)	(0.302)	(0.000)	(0.013)	(0.000)			
Minwage	0.314***	-0.078***	0.055***	-0.012	-0.104***	0.142***	0.027**	0.048***	-0.048***	-0.109***	0.129***	0.615***	-0.550***	0.278***	1.000	
	(0.000)	(0.000)	(0.000)	(0.298)	(0.000)	(0.000)	(0.015)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
AverWage	0.200***	-0.055***	0.138***	-0.017	-0.051***	0.142***	0.007	0.030***	0.014	-0.051***	0.174***	0.588***	-0.539***	0.419***	0.841***	1.000
	(0.000)	(0.000)	(0.000)	(0.118)	(0.000)	(0.000)	(0.519)	(0.007)	(0.209)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Notes: This table reports the Pearson correlations among the variables used in the empirical tests. All variables are defined in detail in Table B.1. *,**, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

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