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Research on the Impact of Climate Policy Uncertainty on Enterprise Digital Transformation

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Abstract

Climate change is one of the major challenges facing the world today, and climate policies are playing an increasingly important role in China's economic system. The uncertainty of climate policies poses risks to investment and market volatility, thereby affecting corporate decision-making and innovation capabilities. Taking Chinese listed companies as the research subjects, this paper empirically analyzes the impact of climate policy uncertainty on corporate digital transformation and its mechanisms at the micro level from 2012 to 2022. The study finds that climate policy uncertainty significantly enhances the digital level of enterprises and promotes digital transformation. Further analysis indicates that internal financing constraints adversely affect the promotion of corporate digital transformation driven by climate policy uncertainty.

Keywords

Climate Policy Uncertainty; Financing Constraints; Digital Transformation

1. Introduction

Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report Synthesis Report: Climate Change 2023 indicates that global warming, sea-level rise, hurricanes, forest fires, and other extreme weather events and abnormal climate occurrences are becoming more frequent, raising public concern and expectations regarding sustainable development at the societal level, while potentially exacerbating social inequalities and environmental problems. In response to the increasingly severe challenges of climate change, China has proposed the goals of "carbon peak and carbon neutrality" and has elevated participation in global climate governance to a national strategic level. Whether and how climate policy uncertainty affects corporate digital transformation—whether promoting or inhibiting it—is a multi-dimensional and complex issue. Frequent fluctuations in climate policies may bring certain risks to enterprises, potentially subjecting them to production, investment, and operational pressures as well as market volatility (Wang Shun et al., 2024; Yu et al., 2021). To this end, this paper explores whether climate policy uncertainty affects corporate digital transformation by combining theoretical analysis with empirical research to examine its impact and further analyze the influencing mechanisms. Finally, based on the empirical results and conclusions, corresponding policy recommendations are proposed to provide useful reference and decision support for other countries in formulating effective climate policies.

This paper focuses on the following aspects: First, expanding theoretical analysis by extending climate risk research from the physical risk dimension to the policy risk dimension, and from macro-policy formulation to micro-enterprise implementation, establishing a theoretical framework to help researchers better explore the impact of climate policy uncertainty on corporate digital transformation, thereby providing theoretical support for understanding its influencing mechanisms. Second, enriching empirical research by revealing the positive impact of climate policy uncertainty on corporate digital transformation, providing a basis for government departments to formulate prudent and proactive climate policies.

2. Theoretical Analysis and Research Hypotheses

2.1. Climate Policy Uncertainty and Corporate Digital Transformation

Climate policy uncertainty affects corporate investment decisions (Robert et al., 2020), while digitalization enhances information processing capabilities. When evaluating project investments, firms often need to consider the future policy environment, including potential carbon emission regulations, renewable energy incentives, and changes in environmental protection laws. If climate policies lack clarity, firms may face higher risks, as an uncertain policy framework complicates long-term investment planning and makes it less predictable (Benthem et al., 2022). When concerns about climate change intensify, investors shift from brown firms to green firms, causing green stocks to outperform brown stocks (Pástor et al., 2021). Furthermore, uncertain climate policies may lead firms to doubt the potential market demand for certain green technologies (Siddique et al., 2023). This skepticism can dampen R&D enthusiasm, making firms more cautious in technological innovation and avoiding substantial investment in areas that may face policy risks. Based on this, this paper proposes:

H1: Climate policy uncertainty can promote corporate digital transformation.

2.2. Climate Policy Uncertainty, Financing Constraints, and Corporate Digital Transformation

Climate policy uncertainty also places pressure on firms when formulating long-term strategies (Mokni et al., 2024). If firms cannot clearly foresee future policy directions, they may adopt a cautious approach toward investment in technological innovation and digital projects. This caution not only affects the adoption of new technologies but may also delay the digital transformation process. Under financing constraints, firms tend to prioritize short-term financial needs, postponing or reducing investment in long-term projects such as digital transformation (Gao et al., 2023). This may put firms at a disadvantage in future market competition, making it difficult to adapt to the rapidly developing digital economy. Based on U.S. survey data, Stroebel and Wurgler (2021) found that climate policy uncertainty has a significant negative impact on corporate financing and operations. Ilhan et al. (2021), examining data on U.S. carbon emissions and options markets, found that climate policy uncertainty directly affects investor expectations for high-carbon firms, generating tail risk and increasing corporate financing costs. In summary, internal financing constraints not only limit firms' resource allocation but also exacerbate the challenges posed by climate policy uncertainty, making firms face greater difficulties and risks in pursuing digital transformation. Based on this, this paper proposes:

H2: Financing constraints inhibit the promoting effect of climate policy uncertainty on corporate digital transformation.

3. Research Design

3.1. Model Construction

To explore the relationship between climate policy uncertainty and corporate digital transformation performance, and to test whether Hypothesis 1 holds, this paper constructs a regression model (1):

$$EDT_{it} = \alpha + \beta CPU_{it} + control_{it} + \lambda_i + \delta_t + \varepsilon_{it} \tag{1}$$

Where EDT_{it} represents the degree of digital transformation of firm i in year t, CPU_{it} is the climate policy uncertainty index value for firm i in year t, $control_{it}$ denotes control variables, λ_i represents firm fixed effects, δ_t represents time fixed effects, ε_{it} is the error term, and standard errors are clustered at the firm level.

To further investigate whether internal financing constraints and external integration of industry and finance have moderating effects on the impact of climate policy uncertainty on corporate digital transformation, a regression model (2) with interaction terms is constructed to test Hypothesis 2, as follows:

$$EDT_{it} = \alpha + \beta_1 CPU_{it} + \beta_2 SA_{it} + \beta_3 CPU_{it} \times SA_{it} + control_{it} + \lambda_i + \delta_t + \varepsilon_{it} \tag{2}$$

Where SA_{it} represents the moderating variable, and the remaining variables are the same as above.

3.2. Variable Definition

(1) Dependent Variable

The dependent variable in this paper is enterprise digital transformation (EDT). Following existing literature, we conducted statistical analysis on the frequency of terms related to digital technology applications, internet business models, intelligent manufacturing, and modern information systems in the annual reports of listed companies (Zhao Chenyu et al., 2021). Considering that many actual data often exhibit right-skewed distributions, we applied a logarithmic transformation to the data, ultimately obtaining the relevant data for enterprise digital transformation.

(2) Core Independent Variable

The independent variable in this paper is climate policy uncertainty (CPU), which refers to various uncertain factors in the formulation and implementation process of climate change-related policies. These factors may affect policy effectiveness, socio-economic conditions, and corporate production activities. Following the methodology of Gavriilidis (2021), we used the Mac BERT model to select relevant judgment words and sentences from climate news in newspapers and periodicals, employing the annual mean of monthly data to measure the annual climate policy uncertainty index (Ren et al., 2022).

(3) Control Variables

The selection of control variables is primarily based on considering potential interfering factors related to enterprise characteristics that may affect digital transformation. We selected control variables that may influence the correlation between climate policy uncertainty and enterprise digital transformation, mainly including enterprise size (Size), asset-liability ratio (Lev), operating revenue growth rate (Growth), fixed assets ratio (Fixed), ownership concentration (Top), duality of roles (Dual), board size (Board), and listing age (Age).

Table 1. Definition of variables

Variables	Identification	Name	Definition
Dependent Variable	*EDT*	Enterprise Digital Transformation	Measured by taking the natural logarithm of one plus the frequency of digitalization-related terms
Independent Variable	*CPU*	Climate Policy Uncertainty	Annual index derived from the arithmetic mean of monthly indices, divided by 100
Control Variables	*Size*	Enterprise Size	Natural logarithm of total enterprise assets
	Lev	Asset-Liability Ratio	Total liabilities / Total assets
	Growth	Operating Revenue Growth Rate	Current year's operating revenue / Previous year's operating revenue - 1
	Fixed	Fixed Assets Ratio	Net fixed assets / Total assets
	Top	Ownership Concentration	Sum of shareholding ratios of the top five shareholders
	Dual	Duality of Roles	Takes the value of 1 if the chairman and general manager are the same person, otherwise 0
	Board	Board Size	Natural logarithm of one plus the number of board directors
	Age	Listing Age	Natural logarithm of one plus the number of years since the enterprise went public

3.3. Data Sources and Descriptive Statistics

This paper takes Chinese listed companies from 2012 to 2022 as the research sample and processes the initial data as follows. First, enterprises that underwent ST and ST* treatment were excluded; second, financial listed companies were removed; finally, enterprise samples with severe missing data were eliminated.

Additionally, all data were winsorized at the 1% level to eliminate the interference of outliers. The macro CPU index was calculated using the MacBERT deep learning model. Data on enterprise digital transformation and related financial characteristic indicators were all sourced from the CSMAR database. The descriptive statistics are shown in Table 2.

Table 2. Descriptive Statistics

Variable	N	Mean	SD	Min	p50	Max
EDT	31,941	3.027	1.261	0.000	3.045	5.861
CPU	31,941	1.815	0.567	0.595	1.796	3.149
Size	31,941	22.27	1.298	19.58	22.08	26.45
Lev	31,941	0.425	0.203	0.0349	0.416	0.908
Growth	31,941	0.160	0.413	-0.658	0.0975	4.024
Fixed	31,941	0.205	0.156	0.00164	0.173	0.719
Top	31,941	33.68	14.74	8.020	31.31	75.78
Dual	31,941	2.115	0.197	1.609	2.197	2.708
Board	31,941	0.290	0.454	0.000	0.000	1.000
Age	31,941	2.944	0.319	1.609	2.996	3.611

4. Empirical Results Analysis

4.1. Baseline Regression Results

The benchmark regression results are reported in Table 3. As can be seen from the empirical results in columns (1) to (4), regardless of whether control variables and fixed effects are included, climate policy uncertainty significantly promotes enterprise digital transformation. Although the coefficient of the core explanatory variable shows a decreasing trend (from 0.204 to 0.030) with the gradual inclusion of control variables and fixed effects, it remains significant at the 1% level throughout. This is consistent with theoretical expectations and demonstrates the robustness of the model specification. Column (4), which fully considers other factors, shows that for each unit increase in climate policy uncertainty, the level of enterprise digital transformation increases by an average of 3.0%, indicating that climate policy uncertainty has a significant promoting effect on enterprise digital upgrading. A possible explanation is that climate policy uncertainty intensifies market competition pressure on enterprises, thereby forcing them to accelerate technological innovation and the implementation of digital strategies. Hypothesis H1 is thus verified.

Table 3. Regression Results

variables	(1)	(2)	(3)	(4)
	EDT	EDT	EDT	EDT
CPU	0.204*** (0.024)	0.129*** (0.022)	0.044*** (0.010)	0.030*** (0.011)
Size		0.178*** (0.015)	0.346*** (0.019)	0.265*** (0.019)
Lev		-0.717*** (0.091)	-0.461*** (0.071)	-0.227*** (0.069)
Growth		0.023 (0.018)	0.049*** (0.010)	0.054*** (0.010)
Fixed		-1.969***	-0.558***	-0.481***

		(0.105)	(0.103)	(0.097)
Top		-0.010*** (0.001)	0.000 (0.001)	-0.000 (0.001)
Board		-0.356*** (0.079)	0.110** (0.051)	0.180*** (0.050)
Dual		0.267*** (0.030)	0.027 (0.018)	0.020 (0.017)
Age		0.060 (0.048)	1.870*** (0.055)	-0.579*** (0.129)
Cons	2.657*** (0.044)	0.363*** (0.326)	-10.210*** (0.388)	-1.416** (0.583)
Firm			YES	YES
Year				YES
N	31,941	31,941	31,941	31,941
R^2	0.008	0.116	0.818	0.829

Note: Standard errors are clustered at the firm level; *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively. This convention is consistently applied throughout the following sections and will not be repeated.

4.2. Endogeneity Treatment - Instrumental Variable Method

The instrumental variable (IV) method is a statistical tool used in regression analysis to address endogeneity issues, typically estimated using two-stage least squares (2SLS). The procedure is as follows: In the first stage, the selected instrumental variable is used to predict the endogenous variable; in the second stage, this predicted value is used as a variable in the regression analysis of the dependent variable. Following the research of Bai et al. (2022), this paper constructs the provincial average level of climate policy uncertainty as an instrumental variable (IV). This approach addresses endogeneity issues arising from policy uncertainty, thereby yielding more reliable estimation results. The results are presented in Table 4, which indicates rejection of the null hypothesis of weak instruments. Meanwhile, in the second-stage regression analysis, the coefficient of the explanatory variable remains significantly positive, further confirming that after addressing endogeneity concerns, climate policy uncertainty continues to significantly promote the process of enterprise digital transformation. These results highlight the important role of climate policy uncertainty in driving enterprise digital transformation.

The prerequisite for using the Difference-in-Differences method is passing the parallel trend test. Following the approach of Beck et al. (2010), if, in the absence of the pilot policy implementation, the outcome variables for the treatment group and the control group do not exhibit systematic bias in their trends over time (Bertrand et al., 2023), this indicates that the parallel trend assumption holds, as specifically illustrated in Figure 1. It can be observed from Figure 1 that prior to the implementation of the pilot policy, the differences in the outcome variables between regions were relatively small, showing a slowly declining trend. Starting from the policy implementation period, the policy effect began to increase significantly, suggesting that the parallel trend assumption is valid. Furthermore, the policy effect became more pronounced in the later stages of implementation. Notably, two years after the establishment of the Big Data Comprehensive Experimental Zones, the treatment effect began to be significantly negative, indicating that the establishment of these zones started to exert a positive growth trend in reducing urban haze pollution and enhancing environmental protection.

Table 4. Endogeneity Test Results

variables	IV-2SLS	
	(1)	(2)
	EDT	EDT
CPU		0.049*** (0.018)
IV	0.988*** (0.010)	
Control	YES	YES
Firm	YES	YES
Year	YES	YES
Kleibergen-Paap rk LM		1371.144
P value		0.000
Kleibergen-Paap rk Wald F		9467.343
N	31,941	31,941
R^2	0.427	0.427

4.3. Robustness Tests

(1) Replacement of the Dependent Variable

Following the research methodology of Wu Fei et al. (2021), this study systematically conducted statistical analysis on 76 digitalization-related word frequencies across five dimensions: artificial intelligence technology, big data technology, cloud computing technology, blockchain technology, and digital technology applications. The resulting word frequency was used as a substitute variable for the dependent variable (EDT2) for re-regression analysis. The regression results are detailed in column (1) of Table 5. The results indicate that climate policy uncertainty has a significant positive impact on enterprise digitalization (EDT2). That is, climate policy uncertainty helps promote enterprise digital transformation and development, consistent with the benchmark regression results, demonstrating the robustness of the model specification.

(2) Exclusion of Other Policy Interferences

During the study period, other policy factors may have influenced enterprise digital transformation. Therefore, to test whether climate policy uncertainty accelerates enterprise digital transformation, this study introduced the impacts of two policies—Big Data Comprehensive Pilot Zones and public data opening—in the robustness tests. This approach aims to enhance the credibility of empirical results and provide a more comprehensive understanding of the role of climate policy uncertainty in enterprise digital transformation. The regression results are presented in columns (2) to (3) of Table 5. The analysis results show that climate policy uncertainty indeed helps promote enterprise digital transformation and development, consistent with the benchmark regression conclusions, further verifying the robustness of the model specification.

Table 5. Robustness Test Results

variables	(1) Replacement of Dependent Variable	(2) Exclusion of Other Policies	(3) Exclusion of Other Policies
CPU	0.034*** (0.013)	0.031*** (0.011)	0.030*** (0.011)
Size	0.255*** (0.022)	0.266*** (0.019)	0.265*** (0.019)
Lev	-0.076 (0.074)	-0.222*** (0.069)	-0.228*** (0.069)
Growth	0.022* (0.012)	0.053*** (0.010)	0.055*** (0.010)
Fixed	-0.446*** (0.104)	-0.484*** (0.097)	-0.481*** (0.097)
Top	-0.005*** (0.001)	-0.000 (0.001)	-0.000 (0.001)
Board	0.215*** (0.057)	0.176*** (0.050)	0.180*** (0.050)
Dual	-0.009 (0.021)	0.020 (0.017)	0.020 (0.017)
Age	-0.143 (0.152)	-0.579*** (0.129)	-0.578*** (0.129)
Big Data Comprehensive Pilot Zone		-0.073*** (0.028)	
Public Data Opening			0.007 (0.019)
Cons	-3.925*** (0.657)	-1.411** (0.584)	-1.418** (0.583)
Firm	YES	YES	YES
Year	YES	YES	YES
N	31,941	31,941	31,941
R^2	0.816	0.829	0.829

5. Moderation Effect Analysis - Internal Financing Constraints

Financing constraints of listed companies may limit their ability to undergo digital transformation during periods of climate policy uncertainty. Financial difficulties can restrict corporate budgets for technological investment and innovation, thereby affecting the speed and effectiveness of their adaptation and transformation. This paper introduces financing constraints (SA) as a moderating variable in studying the impact of climate policy uncertainty on enterprise digital transformation, incorporating the interaction term of financing constraints (SA) and climate policy uncertainty (CPU) into the model to test whether financing constraints have a moderating effect on the promotion of enterprise digital transformation by climate policy uncertainty. The results in columns (1) and (2) of Table 6 show that the coefficient of the interaction term between financing constraints and climate policy uncertainty is negative, indicating that corporate financing constraints are detrimental to enterprise digital transformation under climate policy uncertainty, thus verifying H2.

Table 6. Moderation Effect Results

variables	(1) EDT	(2) EDT
CPU*SA	-0.132*** (0.040)	-0.087** (0.039)
Size	0.328***	0.266***

	(0.020)	(0.019)
Lev	-0.469*** (0.070)	-0.243*** (0.069)
Growth	0.047*** (0.010)	0.052*** (0.010)
Fixed	-0.494*** (0.102)	-0.473*** (0.097)
Top	0.001 (0.001)	0.000 (0.001)
Board	0.115** (0.051)	0.179*** (0.050)
Dual	0.033* (0.018)	0.022 (0.017)
Age	1.049*** (0.093)	-0.591*** (0.130)
Cons	-13.409*** (0.510)	-3.342*** (0.800)
Firm	YES	YES
Year	NO	YES
N	31,920	31,920
R^2	0.822	0.829

6. Conclusions and Recommendations

6.1. Research Conclusions

This paper explores the impact of climate policy uncertainty on enterprise digital transformation and its underlying mechanisms, drawing the following main conclusions:

First, climate policy uncertainty significantly promotes enterprise digital transformation. This conclusion remains valid after robustness and endogeneity tests. The reason lies in the fact that policy uncertainty intensifies environmental and market pressures on enterprises, forcing them to enhance flexibility and responsiveness through digital means to address external challenges.

Second, financing constraints inhibit enterprise digital transformation. Capital shortages make it difficult for enterprises to obtain necessary technical support and external services, weakening their ability to respond to climate policy changes.

6.2. Policy Recommendations

Based on the above conclusions, the following recommendations are proposed:

First, enhance climate policy transparency and flexibility. The government should formulate clear, stable, and dynamically adjustable policy frameworks to reduce enterprises' decision-making pressure when facing uncertainty.

Second, optimize the financing environment and promote the integration of industry and finance. Financial institutions should be encouraged to cooperate with enterprises, providing green financing and special loan support for digital transformation through tax incentives, risk compensation, and other means.

Third, broaden enterprise financing channels. Enterprises should actively explore various methods such as equity financing, debt financing, and crowdfunding to alleviate financing constraints and ensure digital investment.

Fourth, accelerate technological innovation and industrial upgrading. Increase investment in information technology and intelligent fields, promote cross-industry collaboration in energy, environmental protection, big data, etc., and enhance enterprises' technological reserves and core competitiveness in responding to climate policy changes.

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