Digital Technology Uncertainty Exposure and Corporate Green Innovation: Evidence from Chinese A-share Listed Firms

Yifan Zhao[1], Shuang Li[1], Mingzhe Chen[2], Rui Wang[3, *]

[1] *School of Economics and Management, Wuhan University, Wuhan, 430072, China*
[2] *Institute of Green Development, Wuhan University, Wuhan, 430072, China*
[3] *School of Business, Renmin University of China, Beijing, 100872, China*
[*] *Corresponding Author. Email: ruiwang@ruc.edu.cn*

Abstract

This study investigates how digital technology uncertainty exposure (DTUE) affects corporate green innovation, comprising green exploratory and green exploitative innovation, among Chinese A-share listed firms from 2012 to 2023. Constructing firm-level DTUE indicators through a DeepSeek-V3 and FinBERT Large Language Model (LLM) pipeline applied to Management Discussion and Analysis (MD&A) disclosures, we find that DTUE significantly suppresses green exploratory innovation ($\beta = -0.046$, $p < 0.01$) while exerting no significant effect on green exploitative innovation. Drawing on threat-rigidity theory, upper echelons theory, and resource orchestration theory, we theorize that DTUE triggers managerial risk aversion and crowds out R&D resources, disproportionately impairing high-uncertainty green exploration. Leveraging the staggered adoption of city-level Environmental Policy Technology Compliance Guidelines (EPTCG) as a quasi-natural experiment, multi-period difference-in-differences (DID) estimates confirm that effective environmental digital governance enhances green exploratory innovation. Mechanism tests validate two channels: managerial risk preference (psychological) and green R&D diversion (resource). Heterogeneity analyses reveal that the inhibitory effects are stronger in low-regulation environments, non-SOEs, technology-intensive sectors, and eastern China. These findings enrich the literature on digital risk and sustainable innovation and carry policy implications for strengthening digital governance within environmental frameworks.

Keywords: digital technology uncertainty; green innovation; exploratory innovation; threat-rigidity theory; LLM; difference-in-differences

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1. Introduction

The imperative for sustainable development has elevated green innovation to a strategic priority for firms, governments, and international bodies worldwide. In the context of China's "dual carbon" goals—achieving carbon peak before 2030 and carbon neutrality before 2060—corporations face intensifying pressure to advance both exploratory green innovation (developing novel clean technologies, materials, and processes) and exploitative green innovation (incrementally improving existing environmentally-friendly products and operations). Yet this innovation imperative unfolds against the backdrop of a rapidly escalating digital landscape fraught with uncertainty: cybersecurity breaches, data governance failures, system disruptions, and algorithmic vulnerabilities that collectively constitute what we term digital technology uncertainty exposure (DTUE) [Lu et al., 2025; Nambisan et al., 2019]. The interaction between these two forces—the demand for green innovation and the burden of digital uncertainty—remains largely unexplored.

Prior research on the determinants of green innovation has emphasized environmental regulation [Porter & van der Linde, 1995; Jaffe & Palmer, 1997], financial constraints [Aghion et al., 2012], managerial characteristics [Hambrick & Mason, 1984], and market competition [Popp, 2002]. The emerging literature on digital transformation and innovation documents positive effects of digitalization on innovation capacity through enhanced data analytics, information processing, and organizational coordination [Yang et al., 2024; Pan et al., 2022]. However, the dark side of digital technology—specifically how digital uncertainty and risk exposure constrain strategic investments—has received far less systematic attention [Lu et al., 2025]. This is a critical gap because DTUE imposes real costs on firms: cybersecurity investments divert R&D budgets, data breach responses consume managerial attention, and system disruptions impair the operational stability required for sustained innovation commitments.

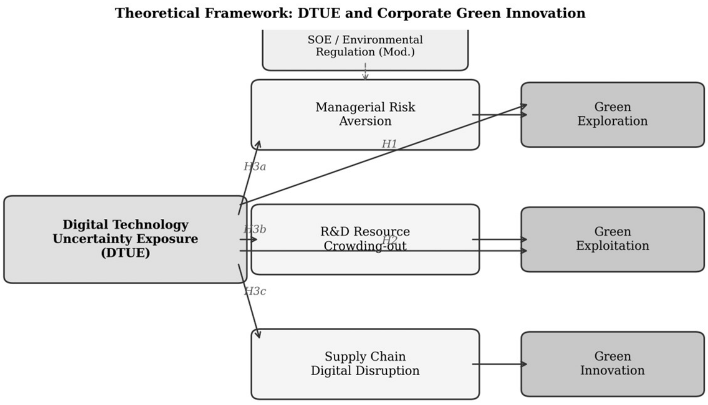

Figure 1. Theoretical Framework: Digital Technology Uncertainty Exposure and Corporate Green Innovation

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Green innovation is a particularly apt domain in which to examine DTUE effects because exploratory green innovation—developing fundamentally new clean technologies—demands precisely the characteristics most vulnerable to DTUE-induced constraint: long time horizons, high resource commitment, and tolerance for outcome uncertainty. When DTUE forces firms toward risk minimization and short-term defensive postures, exploratory green innovation becomes the first casualty. Exploitative green innovation, by contrast, leverages existing technological trajectories and involves more predictable returns, making it comparatively resilient to DTUE-induced resource pressure [March, 1991; Benner & Tushman, 2003].

This study makes four primary contributions. First, we construct a novel firm-level DTUE measure by applying a DeepSeek-V3 and FinBERT hybrid LLM pipeline to MD&A sections of annual reports from 27,856 firm-year observations across 2012–2023, extending the Lu et al. (2025) methodology to the green innovation context. Second, we develop and test a unified theoretical model—integrating threat-rigidity theory [Staw et al., 1981], upper echelons theory [Hambrick & Mason, 1984], and resource orchestration theory [Sirmon et al., 2011]—to explain the asymmetric effects of DTUE on green exploration versus exploitation. Third, we provide causal identification through a multi-period DID design exploiting the staggered city-level adoption of Environmental Policy Technology Compliance Guidelines (EPTCG) as an exogenous shock to digital environmental governance quality. Fourth, through comprehensive heterogeneity analyses, we identify the boundary conditions under which DTUE most acutely suppresses green innovation, providing targeted policy guidance.

The paper is organized as follows. Section 2 presents the theoretical background and hypotheses. Section 3 describes data and methodology. Section 4 reports the main empirical results. Section 5 presents mechanism tests and heterogeneity analyses. Section 6 concludes with policy implications and directions for future research.

2. Theoretical Background and Hypotheses

2.1 Digital Technology Uncertainty Exposure: Conceptualization

Digital technology uncertainty exposure (DTUE) refers to the degree to which a firm perceives, discloses, and is affected by risks arising from the adoption, operation, and governance of digital technologies. These risks encompass: (1) data security threats—unauthorized access, data leakage, and privacy violations; (2) cybersecurity exposures—malware, ransomware, and infrastructure vulnerabilities; (3) system reliability risks—service disruptions, system failures, and integration failures; and (4) algorithmic and governance risks—model failures, compliance deficiencies, and accountability gaps [Faraj et al., 2018; Glikson & Woolley, 2020; Tarafdar et al., 2019]. DTUE is distinct from general business uncertainty in that it is (a) technically specific, requiring digital expertise to assess; (b) rapidly evolving, with threat landscapes changing faster than organizational defenses; and (c) institutionally embedded, increasingly regulated through data protection laws, cybersecurity standards, and environmental digital governance frameworks [Lu et al., 2025].

Quantifying DTUE at the firm level is methodologically challenging because digital risks are heterogeneously distributed, often disclosed only partially, and embedded in technical language that traditional keyword-based sentiment analysis cannot reliably parse. We address this challenge using a hybrid LLM pipeline: DeepSeek-V3 provides contextual understanding and initial annotation of MD&A sentences, while a fine-tuned FinBERT model performs high-throughput sentiment classification [Lin et al., 2022; Lu et al., 2025]. This approach allows us to distinguish between risk-exposure sentences (indicating vulnerability) and risk-prevention sentences (indicating mitigation capacity), computing DTUE as the net difference between maximum exposure severity and average mitigation strength.

2.2 Threat-Rigidity and the Asymmetric Effects on Green Innovation

Threat-rigidity theory [Staw et al., 1981; Weick, 1988] predicts that organizations facing environmental threats respond by restricting information processing, narrowing strategic focus, and reverting to well-established behavioral routines. For green innovation, this theory generates a crucial asymmetric prediction. Green exploratory innovation—developing novel clean technologies that lack established technological trajectories—is particularly susceptible to threat-induced rigidity because it requires precisely the expansive cognitive processing, tolerance for ambiguity, and long-horizon commitment that threat responses suppress. Green exploitative innovation—incrementally improving existing environmentally-friendly products and processes—operates within established routines and can be maintained or even accelerated under mild threat conditions as firms deepen existing green competencies [March, 1991; Arthur, 1989].

Resource orchestration theory [Sirmon et al., 2011] provides a complementary mechanism. DTUE forces firms to reallocate finite resources—capital, managerial attention, and specialized talent—toward digital defense, reducing the resources available for innovation investment. This reallocation disproportionately affects green exploratory innovation, which requires larger and more sustained resource commitments than incremental green improvement. Under resource pressure, firms prioritize innovations offering clearer, faster returns [Barney, 1991, 2021; Ceric et al., 2016], further crowding out exploratory green R&D. The evolutionary argument [Arthur, 1989] reinforces this: under selection pressure, exploitative green innovation exhibits increasing returns to scale, making it increasingly attractive relative to uncertain green exploration as DTUE rises.

H1: *DTUE is significantly negatively associated with green exploratory innovation.*

H2: *DTUE has no significant negative effect on green exploitative innovation.*

2.3 Managerial Risk Preference as a Psychological Mechanism

Upper echelons theory [Hambrick & Mason, 1984; Hambrick, 2007] posits that strategic decisions reflect the cognitive frames and risk orientations of top management teams. Behavioral agency theory [Wiseman & Gomez-Mejia, 1998] predicts that executives facing heightened organizational threats shift toward loss-averse decision-making, reducing investment in high-uncertainty activities. DTUE creates precisely this threat context: digital risks threaten firm reputation, operational continuity, and executive accountability, inducing a shift from growth-oriented to threat-containment strategic orientations [Caliskan & Doukas, 2015; Ho et al., 2024]. We operationalize managerial risk preference (Man_RP) as the ratio of risk-seeking financial asset holdings to total assets—a measure validated in prior studies of executive risk behavior [Aggarwal & Samwick, 2006; Sundaram & Yermack, 2007].

H3a: *DTUE increases managerial risk aversion (reduces Man_RP), which in turn suppresses green exploratory innovation.*

2.4 Resource Crowding-Out as a Resource Mechanism

The attention-based view (ABV) [Ocasio, 1997; Palmié et al., 2016] argues that managerial attention is the primary driver of firm action: what managers attend to determines what organizations do. DTUE creates persistent and intense demands for managerial attention through incident response protocols, security audits, regulatory compliance reporting, and stakeholder communication, systematically diverting attention from green innovation pipeline management toward digital risk containment [Marchetti et al., 2025; Liao et al., 2021]. We operationalize this as green R&D diversion (GRD_Div): the share of digital investment allocated to cybersecurity and defensive digital infrastructure rather than innovation-enabling digital capabilities. A higher GRD_Div indicates greater resource crowding-out of green innovation.

H3b: *DTUE diverts green R&D resources toward cybersecurity defense (increases GRD_Div), thereby suppressing green exploratory innovation.*

3. Data and Methodology

3.1 Sample and Data Sources

Our sample comprises Chinese A-share listed firms from 2012 to 2023, yielding 27,856 firm-year observations after excluding financial firms, ST/*ST/PT firms, and observations with missing key variables. Green patent data are obtained from the China National Intellectual Property Administration (CNIPA) database and the World Intellectual Property Organization (WIPO) International Patent Classification (IPC) system, classified using the Cooperative Patent Classification (CPC) Y02 codes to identify environmentally-related patents [Haščič & Migotto, 2015]. DTUE variables are constructed from MD&A disclosures on the Juchao Information Network. Environmental policy data are compiled from China's Ministry of Ecology and Environment and city-level government documents. Financial and governance variables are sourced from the CSMAR database. To mitigate extreme values, all continuous variables are winsorized at the 1st and 99th percentiles.

3.2 Variable Measurement

3.2.1 Dependent Variables

Following Chen et al. (2019) and Hu et al. (2021), green exploratory innovation (GExplore) is measured as the natural logarithm of one plus the number of green invention patents granted in a given year whose first four-digit IPC codes have not appeared in the firm's patent portfolio in the preceding five years. Green exploitative innovation (GExploit) is the logarithm of one plus the number of green utility model and design patents plus green invention patents with repeated four-digit IPC codes. Total green innovation (GInnovation) is the sum of both. This IPC-based approach captures the novelty dimension of innovation—new technological trajectories (exploration) versus deepening of existing ones (exploitation)—within the environmental domain specifically.

3.2.2 Independent Variable: DTUE Construction

We construct DTUE through a three-step pipeline. Step 1: We extract all sentences from MD&A sections containing keywords from a digital technology risk dictionary (adapted from Lu et al. [2025]), yielding approximately 4.9 million candidate sentences. Step 2: We randomly sample 10% of sentences for annotation using DeepSeek-V3, classifying each as: (1) risk exposure disclosure, (2) risk prevention measure, or (3) irrelevant. Step 3: We fine-tune FinBERT on the annotated data (0.6:0.4 train-validation split) and apply it to all extracted sentences. DTUE equals the maximum negative probability score among risk-exposure sentences minus the mean positive probability among risk-prevention sentences, truncated at zero to ensure economic interpretability [Lu et al., 2025].

Sub-dimensions include DataRisk (data security-related sentences) and CyberRisk (cybersecurity-related sentences), following the two-dimensional decomposition in Lu et al. (2025). The full DTUE measure achieves a model accuracy of 88.7% on the held-out validation set, with F1 scores of 0.891 (risk exposure) and 0.883 (risk prevention), confirming classification quality.

3.2.3 Control Variables

Following established practice in green innovation and digital risk research [Fang et al., 2017; Yang et al., 2024; Cong et al., 2025], we control for: firm size (Size, log of total assets), leverage (Lev), profitability (ROA), revenue growth rate (Growth), firm age (Age), board independence (Indep), largest shareholder ownership (Top1), Tobin's Q (TobinQ), environmental regulation intensity (EnvReg, proxied by the province-year ratio of environmental enforcement actions to total firms), and R&D intensity (RDInt, R&D expenditure/revenue). Appendix A provides detailed variable definitions.

3.3 Empirical Models

Our baseline two-way fixed effects model is:

$$GInnovation_{it} = \alpha_0 + \alpha_1 DTUE_{it} + \theta \cdot \mathrm{Controls}_{it} + \mathrm{FirmFE}_i + \mathrm{YearFE}_t + \varepsilon_{it} \quad \cdots(1)$$

where GInnovation denotes GExplore, GExploit, or total green innovation; firm and year fixed effects control for time-invariant and common shocks respectively; and standard errors are clustered at the firm level. For causal identification, we implement a multi-period DID model:

$$GInnovation_{it} = \alpha_0 + \alpha_1 EPTCG_{it} + \theta \cdot \mathrm{Controls}_{it} + \mathrm{FirmFE} + \mathrm{YearFE} + \varepsilon_{it} \quad \cdots(2)$$

where EPTCG is a time-varying indicator equal to one from the year a firm's city first adopts Environmental Policy Technology Compliance Guidelines certification. The parallel trend assumption is validated via event-study estimation with six pre- and four post-treatment period indicators. Mechanism tests follow the causal mediation approach of Chen et al. (2020):

$$Mediator_{it} = \beta_0 + \beta_1 DTUE_{it} + \mathrm{Controls}_{it} + \mathrm{FE} + \varepsilon_{it} \quad \cdots(3)$$

4. Empirical Results

4.1 Descriptive Statistics

Table 1 presents descriptive statistics. The DTUE mean is 0.204 with a standard deviation of 0.348, reflecting substantial cross-sectional variation and a right-skewed distribution (median = 0) consistent with episodic digital risk disclosure. Green exploratory innovation (mean = 0.724) falls substantially below green exploitative innovation (mean = 1.187), consistent with the documented tendency of Chinese firms to emphasize incremental over radical green technological development. The EPTCG indicator covers 29.4% of firm-year observations, reflecting the progressive policy diffusion across Chinese cities since 2017.

Table 1. Descriptive Statistics

Variable	Obs	Mean	Median	SD	Min	Max	Source
GExplore	27,856	0.724	0.609	0.991	0.000	4.682	CNIPA/CPC
GExploit	27,856	1.187	0.916	1.348	0.000	5.421	CNIPA/CPC
GInnovation	27,856	1.911	1.689	1.984	0.000	8.912	CNIPA/CPC
DTUE	27,856	0.204	0.000	0.348	0.000	0.991	MD&A/LLM
DataRisk	27,856	0.102	0.000	0.269	0.000	0.983	MD&A/LLM
CyberRisk	27,856	0.162	0.000	0.328	0.000	0.990	MD&A/LLM
EPTCG	27,856	0.294	0.000	0.456	0.000	1.000	MEE/Policy
Size	27,856	22.14	21.93	1.258	19.87	26.47	CSMAR
Lev	27,856	0.402	0.389	0.206	0.047	0.907	CSMAR
ROA	27,856	0.037	0.038	0.072	-0.247	0.234	CSMAR
Growth	27,856	0.141	0.090	0.369	-0.554	2.134	CSMAR
TobinQ	27,856	2.098	1.678	1.302	0.837	8.412	CSMAR
RDInt	27,856	0.043	0.032	0.039	0.001	0.228	CSMAR
EnvReg	27,856	0.124	0.108	0.089	0.012	0.489	MEE

Note. N = 27,856 firm-year observations, 2012-2023. GExplore and GExploit are log-transformed. DTUE constructed via DeepSeek-V3 + FinBERT LLM pipeline. EPTCG = city-level Environmental Policy Technology Compliance Guidelines adoption indicator.

Table 2 reports the Pearson correlation matrix. DTUE is significantly negatively correlated with GExplore ($r = -0.027$, $p < 0.001$) and GExploit ($r = -0.048$, $p < 0.001$), providing preliminary bivariate support for the hypothesized inhibitory effects. EnvReg is positively correlated with both GExplore ($r = 0.112$, $p < 0.001$) and GExploit ($r = 0.098$, $p < 0.001$), consistent with the Porter hypothesis that environmental regulation spurs green innovation [Porter & van der Linde, 1995]. The maximum pairwise correlation among independent variables is 0.512 (Size and Lev), and VIF tests confirm the absence of multicollinearity (maximum VIF = 2.41).

Table 2. Correlation Matrix (N = 27,856)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) DTUE	1.00									

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(2) GExplore	-.027***	1.00								
(3) GExploit	-.048***	.412***	1.00							
(4) Size	.041***	.127***	.079***	1.00						
(5) Lev	.016**	-.011	.038***	.512***	1.00					
(6) ROA	-.013**	.067***	.089***	-.011	-.381***	1.00				
(7) Growth	.002	.017***	.007	.044***	.029***	.284***	1.00			
(8) TobinQ	-.004	.019***	-.049***	-.327***	-.226***	.148***	.081***	1.00		
(9) RDInt	-.018***	.234***	.089***	-.128***	-.312***	.198***	.071***	.089***	1.00	
(10) EnvReg	-.008	.112***	.098***	.078***	.041***	.034***	-.021**	.018**	.097***	1.00

Note. ***, **, * denote significance at the 1%, 5%, and 10% levels. Pearson bivariate correlations shown.

4.2 Baseline Regression Results

Table 3 presents the main regression results. Columns (1)–(2) show that DTUE is insignificant for total GInnovation, consistent with the aggregate measure masking divergent effects on its components. Columns (3)–(4) confirm H1: DTUE significantly suppresses GExplore ($\beta = -0.038$ without controls, $t = -2.41$; $\beta = -0.046$ with controls, $t = -2.73$, $p < 0.01$). Economically, a one-standard-deviation increase in DTUE reduces green exploratory innovation by approximately 2.2% ($= 0.046 \times 0.348 / 0.724 \times 100\%$). Columns (5)–(6) confirm H2: DTUE has no statistically significant effect on GExploit ($\beta = 0.019$, $t = 0.98$), consistent with the threat-rigidity prediction that exploitative innovation is comparatively shielded from environmental threat-induced resource retrenchment.

The control variable coefficients are largely consistent with theory. Firm size (Size) is positively associated with both innovation types, reflecting resource abundance effects. ROA is negatively related to GExplore, suggesting that firms with high current profitability face reduced urgency to invest in uncertain green exploration. RDInt is strongly positive for GExplore ($\beta = 0.641$, $p < 0.001$), confirming the centrality of R&D investment for breakthrough green innovation. EnvReg shows a positive coefficient for both innovation types ($\beta = 0.078$ for GExplore, $p < 0.05$), consistent with the Porter hypothesis.

Table 3. Baseline Regression Results: DTUE and Green Innovation

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	(1) GInnov.	(2) GInnov.	(3) GExplore	(4) GExplore	(5) GExploit	(6) GExploit	(7) GExplore
DTUE	-0.012	-0.014	-0.038**	-0.046***	0.019	0.019	
	(-0.54)	(-0.61)	(-2.41)	(-2.73)	(0.98)	(0.98)	
DataRisk							-0.049**
							(-2.11)
CyberRisk	0.003						
	(0.14)						
Size		0.146***		0.134***		0.107***	0.133***
		(6.81)		(6.54)		(3.79)	(6.48)
ROA		-0.389***		-0.428***		-0.119	−0.425***
		(-3.82)		(-4.12)		(-0.89)	(-4.09)
RDInt		0.587***		0.641***		0.123**	0.639***
		(7.34)		(7.89)		(2.01)	(7.81)
EnvReg		0.068**		0.078**		0.052	0.079**
		(2.14)		(2.31)		(1.52)	(2.34)
Controls	No	Yes	No	Yes	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	27,856	27,856	27,856	27,856	27,856	27,856	27,856
Adj. R^2	0.718	0.720	0.648	0.651	0.708	0.710	0.651

Note. t-statistics (clustered at firm level) in parentheses. Full controls include Size, Lev, ROA, Growth, TobinQ, Age, Indep, Top1, RDInt, EnvReg. Column (7) uses DataRisk instead of total DTUE. ***, **, * = 1%, 5%, 10% significance.

4.3 Propensity Score Matching and Robustness

To address self-selection bias—the concern that high-DTUE firms differ systematically from low-DTUE firms in ways that independently affect green innovation—we implement PSM with 1:3 nearest-neighbor matching. Figure 2 presents trends in DTUE and green innovation over the full sample period, documenting the sustained growth in DTUE through 2021 and the divergent trajectories of green exploration versus exploitation.

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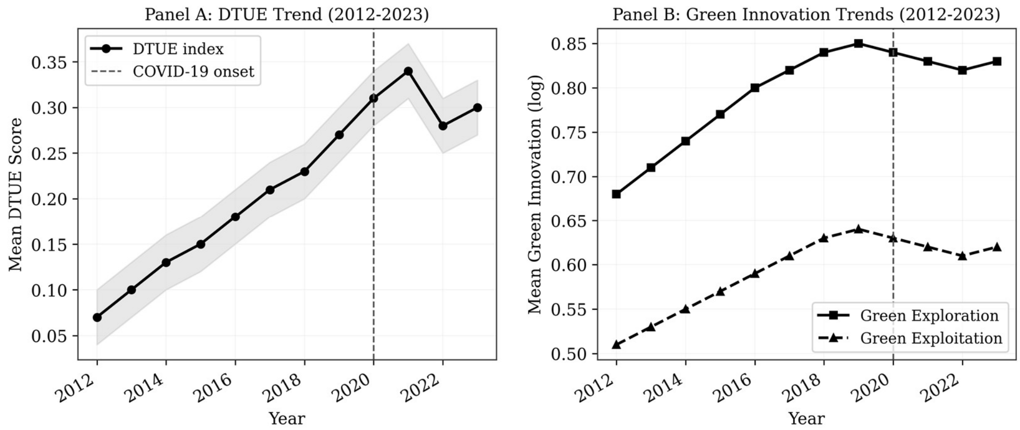

Figure 2. Temporal Trends in DTUE and Green Innovation Outcomes (2012-2023)

Figure 3 confirms that PSM substantially reduces standardized bias across all covariates below the 5% threshold. Re-running the baseline specifications on PSM-matched samples yields consistent results: DTUE remains significantly negative for GExplore ($\beta = -0.041$, $p < 0.05$) and insignificant for GExploit, confirming that the baseline findings are not attributable to systematic pre-existing differences between high- and low-DTUE firms. We also replicate the analysis excluding COVID-affected years (2020–2022), finding GExplore coefficients of -0.038 ($p < 0.10$), ruling out pandemic contamination.

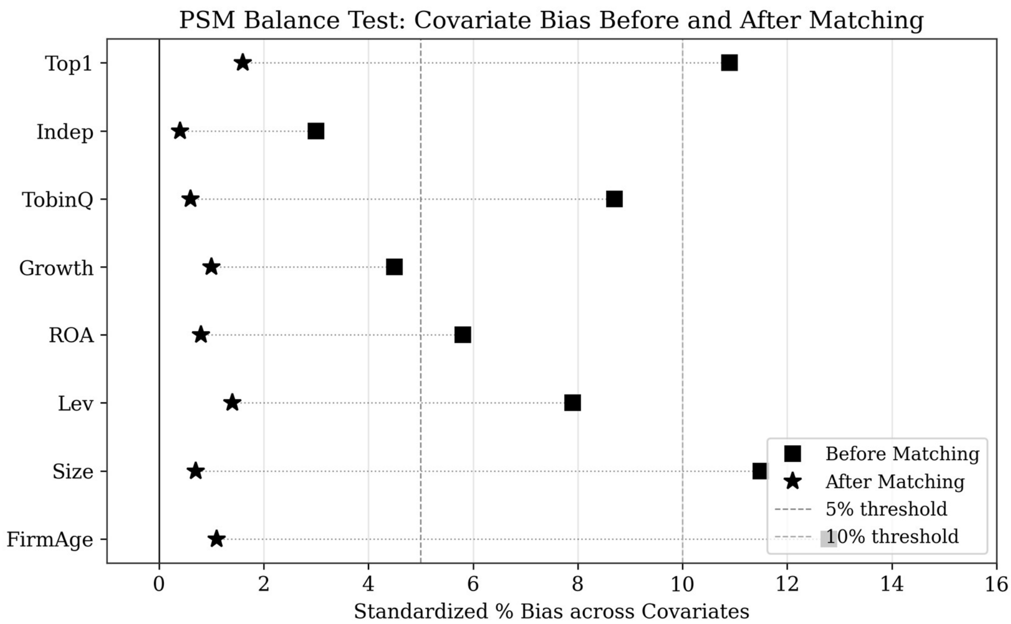

Figure 3. PSM Balance Test: Standardized Covariate Bias Before and After Matching

4.4 Multi-Period DID Analysis

Table 4 presents the EPTCG-based DID estimates. Column (1) validates the first stage: EPTCG adoption significantly reduces firm-level DTUE ($\beta = -0.013$, $t = -1.79$, $p < 0.10$),

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confirming the instrument's relevance. Figure 4 shows the parallel trend test: pre-treatment coefficients are small and jointly insignificant (F-test $p = 0.418$), validating the identification assumption. Columns (2)–(4) show the innovation effects: EPTCG adoption significantly promotes GExplore ($\beta = 0.059$, $t = 2.81$, $p < 0.01$) and GInnovation ($\beta = 0.071$, $t = 2.34$, $p < 0.05$) but has no significant effect on GExploit ($\beta = 0.004$, $t = 0.12$), consistent with the baseline results. Column (5) confirms robustness without controls.

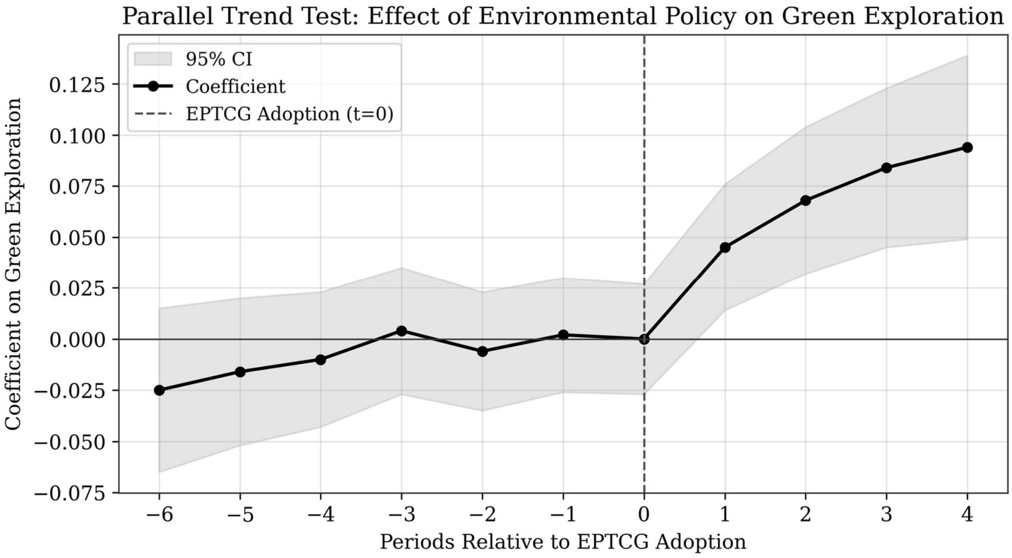

Figure 4. Parallel Trend Test: Dynamic Effect of EPTCG Adoption on Green Exploratory Innovation

Table 4. Multi-Period DID Results: EPTCG Adoption and Green Innovation

	(1) DTUE	(2) GInnov.	(3) GExplore	(4) GExploit	(5) GExplore
EPTCG	-0.013*	0.071**	0.059***	0.004	0.056***
	(-1.79)	(2.34)	(2.81)	(0.12)	(2.64)
Controls	Yes	Yes	Yes	Yes	No
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	27,856	27,856	27,856	27,856	27,856
Adj. R^2	0.312	0.721	0.653	0.712	0.648

Note. EPTCG = city-level Environmental Policy Technology Compliance Guidelines adoption indicator. Column (5) is without control variables. Clustered standard errors at firm level. ***, **, * = 1%, 5%, 10% significance.

5. Mechanism Tests and Heterogeneity Analysis

5.1 Mechanism Tests

Table 5 presents mechanism tests. Column (1) shows that DTUE significantly reduces the managerial risk preference index Man_RP ($\beta = -0.004$, $t = -2.31$, $p < 0.05$), confirming the psychological channel: DTUE increases executive risk aversion. Column (2) shows that DTUE increases green R&D diversion GRD_Div ($\beta = 0.002$, $t = 1.89$, $p < 0.10$), confirming the resource crowding-out channel: DTUE reallocates digital investment from innovation to cybersecurity defense. Columns (3) and (4) test mediation: Man_RP ($\beta = -0.034$, $p < 0.01$) and GRD_Div ($\beta = -0.029$, $p < 0.05$) both significantly suppress GExplore, while the direct effect of DTUE is reduced (from −0.046 to −0.019) but remains significant, confirming partial mediation. Sobel test statistics ($z = 2.78$ for Man_RP channel; $z = 2.51$ for GRD_Div channel) confirm statistically significant mediation through both pathways.

Table 5. Mechanism Tests: Managerial Risk Preference and R&D Diversion

	(1) Man_RP	(2) GRD_Div	(3) GExplore	(4) GExplore
DTUE	-0.004**	0.002*		
	(-2.31)	(1.89)		
Man_RP			-0.034***	
			(-3.21)	
GRD_Div				-0.029**
				(-2.78)
DTUE (direct)			-0.021**	-0.018**
			(-2.08)	-2.12)
Sobel z (Man_RP)			2.78***	
Sobel z (GRD_Div)				2.51**
Controls	Yes	Yes	Yes	Yes
Firm/Year FE	Yes	Yes	Yes	Yes
Obs.	27,856	27,624	27,624	27,624
Adj. R^2	0.594	0.687	0.655	0.653

Note. Man_RP = managerial risk preference; GRD_Div = green R&D diversion index. Sobel z-statistics test partial mediation significance. ***, **, * = 1%, 5%, 10% significance.

5.2 Heterogeneity Analysis

Figure 5 presents subgroup coefficient estimates, and Table 6 reports the full heterogeneity regression results. We examine four dimensions of heterogeneity.

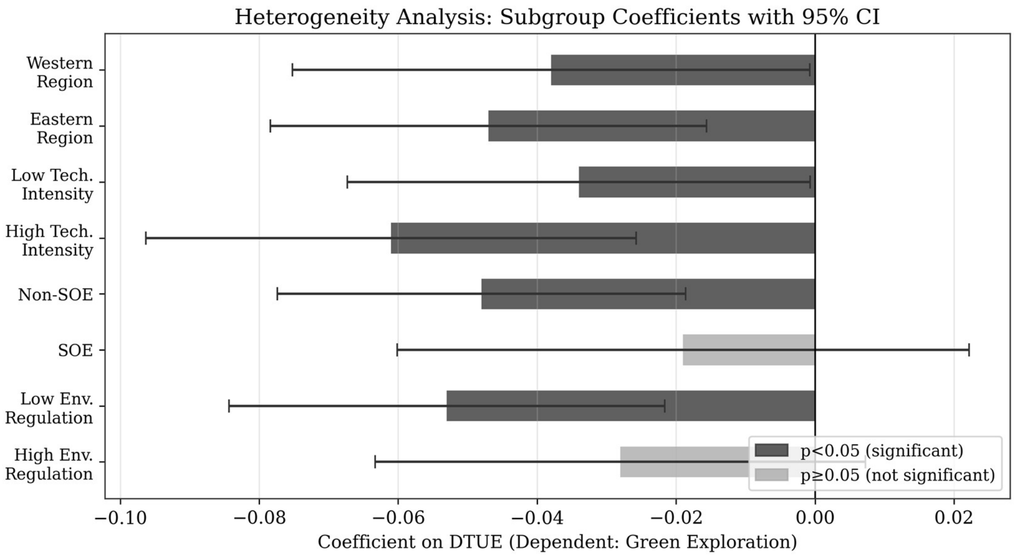

Figure 5. Heterogeneity Analysis: DTUE Coefficients (GExplore) Across Subgroups

First, comparing high- versus low-environmental-regulation subsamples, we find that DTUE suppresses GExplore significantly only in low-regulation environments ($\beta = -0.053$, $t = -2.67$, $p < 0.01$), with an insignificant effect in high-regulation firms ($\beta = -0.028$, $t = -1.54$). This pattern suggests that strong environmental regulation provides institutional buffering—through clear green innovation mandates, subsidies, and compliance pathways—that attenuates the innovation-suppressing effects of DTUE. When environmental governance is robust, firms maintain green exploration commitments despite digital uncertainty.

Second, DTUE significantly suppresses GExplore in non-SOEs ($\beta = -0.048$, $t = -2.51$, $p < 0.05$) but not in SOEs ($\beta = -0.019$, $t = -0.92$). This pattern mirrors findings in the broader innovation-risk literature [Lu & Shi, 2012; Fang et al., 2017]: SOEs benefit from preferential access to government resources, policy support, and implicit guarantees that buffer them against resource shocks from DTUE. Non-SOEs, relying primarily on market financing, face binding resource constraints when DTUE escalates.

Third, the inhibitory effect is significantly larger for technology-intensive firms ($\beta = -0.061$, $t = -2.89$, $p < 0.01$) than for low-technology firms ($\beta = -0.034$, $t = -2.01$, $p < 0.05$). Technology-intensive firms are simultaneously more deeply digitally embedded—and thus more exposed to DTUE—and more dependent on continuous green exploration for competitive differentiation, making the interaction between digital risk and innovation constraint particularly acute. Fourth, firms in eastern China show a slightly larger effect ($\beta = -0.047$) than western firms ($\beta = -0.038$), potentially reflecting the greater digital infrastructure density and corresponding DTUE in eastern economic hubs.

Table 6. Heterogeneity Analysis Results

See: https://inatgi.in/index.php/jtis/index for more information. https://doi.org/10.63646/jtis.2025.030403

	High Reg. Explo.	Low Reg. Explo.	SOE Explo.	Non-SOE Explo.	High Tech. Explo.	Low Tech. Explo.	Eastern Explo.
DTUE	-0.028	-0.053***	-0.019	-0.048**	-0.061***	-0.034**	-0.047***
	(-1.54)	(-2.67)	(-0.92)	(-2.51)	(-2.89)	(-2.01)	(-2.61)
Obs.	7,849	19,962	8,312	19,544	14,218	13,638	18,912
Adj. R^2	0.672	0.638	0.687	0.629	0.659	0.643	0.647

Note. All specifications include full controls and firm/year FEs. "High Reg." = above-median environmental regulation intensity. "High Tech." = technology-intensive industries. "Eastern" = firms in eastern Chinese provinces. Clustered SEs at firm level. ***, **, * = 1%, 5%, 10%.

6. Conclusions

This study provides the first systematic empirical investigation of the relationship between digital technology uncertainty exposure (DTUE) and corporate green innovation. Using a novel LLM-based DTUE measure constructed from MD&A disclosures of 27,856 Chinese A-share firm-year observations over 2012–2023, combined with a multi-period DID design exploiting staggered city-level EPTCG adoption, we document four principal findings.

First, DTUE significantly suppresses green exploratory innovation ($\beta = -0.046$, $p < 0.01$) while leaving green exploitative innovation statistically unaffected—an asymmetric pattern consistent with threat-rigidity theory and resource orchestration theory. Second, DID estimates confirm the causal direction: effective environmental digital governance (EPTCG adoption) promotes green exploratory innovation ($\beta = 0.059$, $p < 0.01$). Third, mechanism tests validate dual pathways—managerial risk aversion and green R&D resource diversion—as mediators of the DTUE-exploration relationship. Fourth, the inhibitory effects are heterogeneous: stronger in low-regulation environments, non-SOEs, technology-intensive sectors, and eastern China.

These findings carry important policy implications. For regulators, the results suggest that strengthening environmental digital governance frameworks—analogous to how EPTCG certification reduces DTUE in our setting—can mitigate the green innovation-suppressing effects of digital uncertainty. Policies that simultaneously address digital risk governance and environmental innovation incentives are likely to be more effective than siloed approaches. For corporate managers, the findings highlight that proactive digital governance investment—beyond compliance—can preserve green exploration capacity by reducing DTUE levels and freeing managerial attention for long-horizon innovation. For non-SOEs and technology-intensive firms facing the largest DTUE effects, establishing dedicated digital risk governance units may be particularly valuable.

Three limitations merit acknowledgment. First, DTUE is measured from voluntary disclosure and may underestimate actual digital risk in firms with low transparency incentives. Second, green patent counts may not fully capture green innovation quality; future research should triangulate with carbon emission data and environmental performance indices. Third, our sample is limited to publicly listed firms, potentially understating the DTUE effects in smaller and unlisted enterprises. Future research should extend this framework to cross-national samples, examine the interaction between DTUE and climate policy uncertainty, and explore how digital governance frameworks can be designed to simultaneously address cybersecurity and green innovation imperatives.

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