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Climate risk, sectoral technological progress and corporate profitability in the US: an ADL-MIDAS forecasting approach

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Abstract

Purpose – This study examines how physical and transition climate risks affect US sectoral corporate profitability and whether sectoral technological progress, proxied by green innovation, improves the predictability of profits under climate uncertainty.

Design/methodology/approach – Using a mixed-frequency dataset covering 2000Q1–2024Q1, the analysis combines quarterly corporate profits for 11 US Global Industry Classification Standard sectors with daily physical and transition climate risk indices and quarterly green patent activity. An Autoregressive Distributed Lag–Mixed Data Sampling (ADL-MIDAS) framework is employed to capture the dynamic effects of high-frequency climate risks on quarterly profits across short- (4 quarters), medium- (8 quarters) and long-term (12 quarters) horizons. Out-of-sample forecast performance is evaluated using the Campbell–Thompson and Clark–West tests.

Findings – The results show that both physical and transition climate risks contain significant predictive information for sectoral profitability, with substantial heterogeneity across industries. Carbon-intensive sectors such as Energy and Industrials exhibit stronger sensitivity, while Financials and Communication Services display comparatively weaker responses. Incorporating green innovation improves forecast accuracy across most sectors, particularly in innovation-intensive industries such as Information Technology, Health Care and Real Estate.

Originality/value – This study contributes to the climate–finance literature by jointly integrating climate risks and sectoral technological progress within a mixed-frequency forecasting framework. It demonstrates that accounting for green innovation enhances the predictive performance of climate risk models, offering practical value for investors, risk managers and policymakers concerned with monitoring sectoral exposure to climate-related risks.

Keywords Climate risk, Green innovation, Sectoral profitability, ADL-MIDAS, United States

Paper type Research article

1. Introduction

The growing economic relevance of climate change has intensified scholarly and policy attention on its implications for corporate performance and financial stability. Climate-related shocks ranging from extreme weather events and natural disasters to persistent temperature anomalies affect firms through multiple transmission channels. These include physical damages to assets, disruptions in production and supply chains, changes in energy demand, and valuation losses in financial markets (Ginglinger and Moreau, 2019; Kling *et al.*, 2021; Pankratz *et al.*, 2023; Cevik and Miryugin, 2023). At the macroeconomic level, such shocks can generate systemic risks by lowering productivity, amplifying uncertainty, and heightening

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volatility in asset prices and profits. A growing body of empirical evidence confirms that physical climate risks adversely affect firm earnings, profitability, and earnings volatility across industries and geographies (Fuss, 2016; Huang *et al.*, 2018; Ding *et al.*, 2021; Addoum *et al.*, 2023). Consistent with this view, Huang *et al.* (2025a) show that climate change risks significantly constrain firm entry by increasing financial and operational uncertainty, highlighting the systematic nature of climate-related economic shocks.

From a theoretical standpoint, the link between climate shocks and corporate profitability can be understood through the Arbitrage Pricing Theory (APT) and real options theory. Within the APT framework, climate risks represent systematic factors influencing expected returns and risk premia (Pástor *et al.*, 2021). Firms with greater exposure to climate vulnerabilities may face higher cost of capital or demand a risk premium as compensation for non-diversifiable risks. Meanwhile, real options theory posits that in the face of uncertainty—such as future climate policy shifts or transition costs—firms may delay, adjust, or stage investments to preserve value and minimize losses (Bloom, 2009; Bolton and Kacperczyk, 2021). Together, these frameworks imply that climate shocks affect firm value not only through realized financial losses but also through shifts in expectations, investment timing, and managerial risk-taking behaviour.

Despite the growing literature, most studies model climate risk as an exogenous shock, treating firms as passive recipients rather than adaptive agents. This perspective overlooks the potential role of technological innovation, especially green innovation, as a factor that may be associated with differences in how climate risks are reflected in sectoral profitability. Technological progress enhances firms' adaptive capacity, operational efficiency, and long-term competitiveness. Firms investing in low-carbon technologies and sustainable production processes can reduce emissions, improve resilience, and capture new market opportunities in the green economy (Wang *et al.*, 2018; Liu *et al.*, 2024). Empirical evidence also suggests that environmental pressures can stimulate adaptive firm responses. Ullah and Mazhar (2024), for example, find that stringent environmental regulations are associated with enhanced enterprise growth, supporting the notion that innovation can transform climate-related challenges into profitability opportunities.

However, empirical analyses that integrate climate risks with firm-level or sectoral innovation indicators remain limited. Existing studies largely focus on contemporaneous relationships between climate variables and firm outcomes, often neglecting dynamic predictive frameworks. Furthermore, sectoral heterogeneity in both climate exposure and innovation intensity remains underexplored. For instance, energy-intensive sectors such as Energy, Materials, and Industrials face direct physical and regulatory risks, while service-oriented sectors like Financials, Real Estate, and Information Technology experience climate risk indirectly through valuation channels, financing structures, or technological dependencies (Addoum *et al.*, 2023; Cevik and Miryugin, 2023). Examining how these sectors respond differentially to climate and technological shocks provides a more comprehensive understanding of macro-financial stability and the pathways of economic adaptation.

This study extends the literature by jointly analyzing the predictive relationship between climate risk and sectoral corporate profitability across eleven US sectors. We further examine whether the inclusion of green innovation proxied by OECD-based green patent activity enhances forecast accuracy and explanatory power. The analysis distinguishes between physical climate risk (PCR), encompassing temperature anomalies and natural disasters, and transition climate risk (TCR), reflecting climate policy uncertainty and regulatory events, based on indices developed by Faccini *et al.* (2021). These daily indices are combined with quarterly corporate profit data spanning 2000Q1–2024Q1, resulting in a rich mixed-frequency dataset suitable for dynamic analysis.

To effectively model the interaction between daily and quarterly variables, we employ the Autoregressive Distributed Lag–Mixed Data Sampling (ADL-MIDAS) framework (Salisu and Ogbonna, 2019). This approach enables efficient integration of high-frequency climate data into low-frequency profit forecasts, avoiding information loss common in data aggregation. The ADL-MIDAS framework captures both short-term and long-term dynamics and allows for flexible lag structures that align with the temporal diffusion of climate shocks. In addition, out-of-sample forecast evaluation using the Clark–West (2007) test ensures the robustness of predictive gains from including green innovation relative to benchmark autoregressive models.

This paper contributes to the literature in three key ways. First, it provides a comprehensive sectoral analysis of how physical and transition climate risks influence corporate profitability across multiple industries, revealing heterogeneous sensitivities and adjustment patterns. Second, it integrates technological innovation into the forecasting structure, showing that innovation improves predictive accuracy and helps capture additional variation in sectoral profitability, consistent with evidence from Ullah and Mazhar (2024). Third, it advances the methodological application of mixed-frequency econometrics in climate–finance research, demonstrating its usefulness for short- and medium-term forecasting under environmental uncertainty.

Beyond its academic contributions, this study carries significant practical and policy implications. For investors and portfolio managers, understanding the joint behaviour of climate and technological shocks can improve risk pricing, portfolio diversification, and strategic asset allocation. For corporate managers, the results underscore the importance of green innovation as a tool for maintaining profitability and competitiveness in a transitioning economy. For policymakers, the results highlight how incorporating technological indicators into forecasting frameworks can improve the monitoring of sectoral exposure to climate-related risks.

Moreover, recent contributions emphasize the role of green fiscal policy, fiscal decentralization, and green finance in shaping firm-level adjustment and efficiency outcomes. For example, evidence shows that green fiscal policy instruments—such as subsidies, tax incentives, and environmental levies—can improve firms' investment efficiency and promote green innovation, particularly among heavily polluting industries (see Huang *et al*., 2025b). Similarly, fiscal decentralization has been found to influence firms' environmental performance and low-carbon transition through improved resource allocation, policy flexibility, and innovation incentives (Gao *et al*., 2025). In addition, emerging evidence indicates that green finance may strengthen the transmission of environmental policies to firm-level outcomes by easing financing constraints and facilitating green transformation processes (Du *et al*., 2026). These findings underscore the importance of institutional and policy channels in shaping how firms are exposed to and adjust to climate-related risks. Incorporating these perspectives provides a broader context for interpreting the role of green innovation—not merely as a technological indicator, but as part of a wider policy and financial ecosystem influencing sectoral performance.

The remainder of the paper is structured as follows. Section 2 discusses the data and preliminary statistics. Section 3 presents the econometric methodology and estimation procedure. Section 4 reports empirical results and forecasting evaluations. Section 5 concludes with practical and policy implications.

2. Data and preliminary result

This study utilizes a novel mixed-frequency dataset spanning the period from 2000Q1 to 2024Q1, integrating quarterly US *sector*-level corporate profits, daily climate risk indicators, and quarterly green innovation data. The corporate profit data are obtained from Bloomberg's proprietary database and encompass all eleven Global Industry Classification Standard (GICS) sectors: Communication Services, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Real Estate, and Utilities. These sector-level profit series combine publicly reported financial statements, analyst consensus forecasts, and Bloomberg's standardized adjustments, ensuring consistency and comparability across both sectors and time.

The daily climate risk indicators are derived from the Climate Risk Index (CRI) framework developed by Faccini *et al*. (2021). This framework differentiates between physical climate risks—such as temperature anomalies and extreme weather events—and transition climate risks stemming from climate policy uncertainty and international environmental negotiations. To condense these high-frequency and high-dimensional data, Principal Component Analysis (PCA) is applied, yielding two composite indices: Physical Climate Risk (PCR) and Transition Climate Risk (TCR). This dimensionality reduction preserves the essential informational content while ensuring tractability for the mixed-frequency ADL-MIDAS estimation.

To capture sectoral technological adaptation to climate challenges, we employ a quarterly green innovation index derived from the OECD ENV-TECH database. The index measures the number of patent families classified under the Y02 International Patent Classification subclasses, which represent technologies designed to mitigate climate change across the energy, transport, building, and industrial domains. Since the original data are reported annually (2000–2023), we apply linear interpolation to construct quarterly estimates suitable for MIDAS regressions. This harmonized frequency structure allows for a nuanced, sector-specific assessment of how climate risks and technological innovation jointly shape corporate profitability.

Table 1 presents the descriptive statistics for the key variables—quarterly sectoral profits, daily climate risk indices, and quarterly green innovation—highlighting the variability and dynamic relationships that motivate the subsequent ADL-MIDAS analysis.

The descriptive statistics indicate that the Financials sector has the highest average profits, followed by Communication Services, while Real Estate and Materials exhibit the lowest averages, reflecting differences in sectoral scale and climate exposure. The Energy sector shows extreme volatility, with the largest range and highest standard deviation, driven by global markets, geopolitical events, and climate policy shocks. Skewness and kurtosis suggest heavy tails and asymmetry in Energy, Real Estate, and Industrials, indicating vulnerability to extreme events.

The Physical Climate Risk index is positively skewed and leptokurtic, indicating infrequent but severe disruptions. Transition Climate Risk exhibits even greater variability, reflecting episodic but impactful regulatory or market shifts, such as carbon pricing or international climate negotiations. The green innovation index displays moderate variation with mild left skewness, suggesting a generally stable trend in environmentally oriented technological progress, punctuated by occasional innovation surges.

These distributional properties justify the use of ADL-MIDAS models, which accommodate mixed data frequencies and non-normal distributions. The dataset's combination of high-frequency climate risk indicators and quarterly corporate outcomes allows for dynamic, sector-specific estimation of profit responses to both climate shocks and green innovation.

3. Methodology

3.1 Theoretical framework

The relationship between climate risk and corporate profits can be conceptualized through multiple theoretical lenses. Arbitrage Pricing Theory (APT) provides a foundation by treating climate risk as a systematic factor affecting firm profitability. However, APT alone cannot fully capture the complexity of climate-related shocks, which include regulatory changes, shifting consumer preferences, and physical damages that increase operational costs or reduce revenues. To complement APT, stakeholder theory emphasizes that firms actively engaged in environmental management often achieve better financial performance (Albertini, 2013; Feng *et al*., 2016). Firms investing in climate initiatives may protect shareholder value, whereas those heavily exposed to climate risks face higher costs and may require adaptation technologies (Semenova and Hassel, 2016; Ozkan *et al*., 2023). Using the physical (PCR) and

Table 1. Descriptive statistics

	Mean	Max	Min	Std. dev	Skewness	Kurtosis	Start date	End date	No. Obs
Quarterly sectoral corporate profits (profit after tax [net profits])									
Communication	1089.75	3173.94	−615.14	742.28	0.89	3.46	Mar-2000	Dec-2024	100
Consumer discretionary	320.52	807.41	−174.90	201.28	0.48	2.94	Mar-2000	Dec-2024	100
Consumer staple	615.13	998.39	287.32	171.96	0.13	2.46	Mar-2000	Dec-2024	100
Energy	669.72	2709.34	−6481.22	1059.12	−3.35	22.81	Mar-2000	Dec-2024	100
Financial	1317.08	4223.57	−2485.11	1182.22	−0.27	3.77	Mar-2000	Dec-2024	100
Health care	421.67	720.22	169.26	142.28	0.09	1.84	Mar-2000	Dec-2024	100
Industrial	371.70	875.21	73.64	142.70	1.31	5.38	Mar-2000	Dec-2024	100
Information technology	577.49	1597.49	−7.94	345.89	0.85	3.01	Mar-2000	Dec-2024	100
Materials	222.38	694.73	−13.76	145.08	0.90	3.45	Mar-2000	Dec-2024	100
Real estate	188.00	1090.46	−8.97	216.21	2.86	10.44	Mar-2000	Dec-2024	100
Utility	320.16	618.60	−6.27	87.65	−0.15	4.60	Mar-2000	Dec-2024	100
Daily climate risk index									
Physical climate risk	0.5359	5.3804	0.0001	0.6220	2.3069	10.3319	1/3/2000	12/31/2024	7,691
Transition climate risk	0.6373	12.1436	0.0001	0.8601	3.4552	23.2404	1/3/2000	12/31/2024	7,691
Quarterly control variable (green innovation index)									
Green innovation	99.01	137.73	53.47	17.01	−0.18	2.69	Mar-2000	Dec-2024	100

Note(s): Max, Min and Std. Dev. means maximum, minimum, and standard deviation, while No. Obs. is number of observations transition (TCR) climate risk indices developed by Faccini *et al*. (2021), we examine how sectoral profits respond to climate shocks while controlling for green innovation, which captures sectoral technological progress aimed at mitigating climate risks.

3.2 Model specification

To assess the predictive power of climate risk on corporate profits, we begin with a bivariate predictive model:

$$PROFIT_t = \alpha + \beta CRISK_{t-1} + \varepsilon_t \tag{1}$$

where $\text{PROFIT}_{i,t}$ denotes net profits after tax for sector i at quarter t, and $\text{CRISK}_{i,t}$ represents either physical (PCR) or transition (TCR) climate risk. While this model provides a baseline, it is restrictive because it does not account for persistence in profits or the dynamic influence of past climate shocks.

Following Salisu and Ogbonna (2019), we adopt the Autoregressive Distributed Lag–Mixed Data Sampling (ADL-MIDAS) framework, which models dynamics in both dependent and independent variables while accommodating mixed data frequencies. Standard ADL models capture quarterly profit persistence but cannot incorporate daily climate risk indicators effectively. ADL-MIDAS resolves this by allowing daily PCR and TCR observations to influence quarterly profits, preserving high-frequency information. The general ADL-MIDAS specification can be expressed as:

$$PROFIT_{i,t} = \varphi + \sum_{p=1}^{P} \alpha_p PROFIT_{i,t-p} + \sum_{d=0}^{D} \theta_d f(CRISK_{i,t-d}) + \varepsilon_{t+1} \tag{2}$$

where P and D are the number of lags for the quarterly profits and daily climate risk, respectively, and $f(\cdot)$ represents the weighting scheme applied to daily observations. We use an exponential Almon lag polynomial, which flexibly assigns weights to daily data, capturing the most informative lags while avoiding parameter proliferation.

To account for the potential influence of technological progress, we include green innovation as an additional predictor in the ADL-MIDAS framework:

$$PROFIT_{i,t} = \varphi + \sum_{p=1}^{P} \alpha_p PROFIT_{i,t-p} + \sum_{d=0}^{D} \theta_d f(CRISK_{i,t-d}) + \lambda GREEN_{i,t} + \varepsilon_{t+1} \tag{3}$$

where $\text{GREEN}_{i,t}$ is the quarterly green innovation index. This specification allows us to assess the predictive power of climate risk on sectoral profits while controlling for the role green innovation as an additional predictor. Forecast performance is then compared against models excluding green innovation and against an AR(1) benchmark:

$$PROFIT_t = \alpha + \lambda PROFIT_{t-1} + \varepsilon_t; \tag{4}$$

where λ is the first order autoregressive coefficient and is expected to satisfy the stationarity condition of $|\rho| < 1$.

It is important to note that the lag length for the quarterly autoregressive component is selected using the Akaike Information Criterion (AIC), while the optimal lag structure for the MIDAS component is determined through a grid search over alternative lag specifications. The exponential Almon lag polynomial is employed to parsimoniously capture the weighting scheme of high-frequency (daily) climate risk observations.

3.3 Forecast performance evaluation measure

We assess the predictive ability of climate risk using rolling-window out-of-sample forecasts, with 75% of the sample used for estimation and 25% for forecasting. Forecast horizons range from 1 to 12 quarters. Forecast accuracy is measured using the Campbell and Thompson (2008) test, which compares model predictions against a historical average, and the Clark and West (2007) test, which corrects for bias in forecast error variance when comparing nested models. Let MSE_U and MSE_R denote the mean squared errors of the unrestricted model (ADL-MIDAS including green innovation) and the restricted model (ADL-MIDAS without green innovation or AR(1)), respectively. A positive Campbell-Thompson statistic indicates superior predictive performance of the unrestricted model. The Clark-West test provides statistical confirmation of differences in forecast accuracy. For each period t, the adjusted squared error is calculated as:

$$f_t = \left(y_t - \widehat{y}_{R,t}\right)^2 - \left[\left(y_t - \widehat{y}_{U,t}\right)^2 - \left(\widehat{y}_{U,t} - \widehat{y}_{R,t}\right)^2\right] \tag{5}$$

where y_t is realized profit, and $\widehat{y}_{U,t}$, $\widehat{y}_{R,t}$ are predictions from the unrestricted and restricted models. The t-statistic of the average f_t tests whether including green innovation significantly improves forecast accuracy.

4. Result presentation

4.1 Corporate profit–climate risk nexus (without green innovation)

Table 2 presents the estimated predictive relationships between physical (PCR) and transition (TCR) climate risks and sectoral corporate profits, without controlling for green innovation. The results indicate that both risk measures contain statistically significant predictive information for profits, with substantial heterogeneity across sectors. Physical climate risk (PCR) is generally associated with lower predicted profitability in carbon-intensive sectors such as Energy, Industrials, and Information Technology. The partial distributed lag (PDL) estimates suggest that these associations accumulate over time, particularly in the Energy sector, indicating that lagged climate risk measures contain incremental information for forecasting future profits. In contrast, Financials and Materials display mixed predictive patterns, including positive associations in some specifications. These findings should be interpreted cautiously as reflecting co-movement or sector-specific exposure rather than economic gains from climate risk itself. Such patterns may capture differences in sectoral composition, pricing dynamics, or financial market channels embedded in the data.

Transition climate risk (TCR), which reflects variation in climate policy uncertainty and related developments, also exhibits heterogeneous predictive relationships across sectors. Negative associations are observed in sectors such as Energy, Consumer Discretionary, and Industrials, while positive associations appear in Communication Services and Financials. The estimated PDL terms indicate that the predictive content of TCR is distributed over multiple quarters, suggesting that lagged transition risk measures contribute to forecasting performance over time. In sum, the results in Table 2 highlight the importance of sectoral heterogeneity in the predictive relationship between climate risk and corporate profitability. Sectors such as Energy and Industrials exhibit stronger sensitivity in terms of forecast responses, whereas Communication Services and Financials display comparatively weaker or mixed patterns. These findings underscore the relevance of incorporating forward-looking climate risk indicators in forecasting models of sectoral profits.

4.2 Corporate profit–climate risk nexus: controlling for green innovation

Tables 3 and 4 present the results when green innovation is included as a control variable in the ADL-MIDAS models. This allows us to examine whether sector-level technological progress

Table 2. Results for sectoral corporate profits and climate risk nexus without the role of green innovation

Sector	Physical climate risks $\boldsymbol{Profit_{t-1}}$	$\boldsymbol{Crisk_t}$	Lag	PDL01	PDL02	Transition climate risks $\boldsymbol{Profit_{t-1}}$	$\boldsymbol{Crisk_t}$	Lag	PDL01	PDL02
Communication service	0.7503***	−0.1750**	2	−0.4446*	0.2695*	0.7341***	0.2234***	2	0.6079***	−0.3844***
	(0.0808)	(0.0850)		(0.2350)	(0.0157)	(0.0792)	(0.0837)		(0.2165)	(0.1381)
Consumer discretionary	0.6738***	0.0546***	2	0.1534**	−0.0988**	0.5980***	0.0549***	2	0.1806***	−0.1258***
	(0.0844)	(0.0204)		(0.0625)	(0.0434)	(0.0826)	(0.0185)		(0.0550)	(0.0384)
Consumer staple	0.7593***	0.0380***	3	0.0624**	−0.0244*	0.7574***	0.0407***	2	0.1166***	−0.0759**
	(0.0676)	(0.0123)		(0.0245)	(0.0126)	(0.0704)	(0.0146		(0.0435)	(0.0305)
Energy	0.1977*	−0.4438*	2	−1.3809**	0.9370**	0.2045*	0.4929***	2	1.3507***	−0.8577***
	(0.1100)	(0.2345)		(0.6928)	(0.4743)	(0.1057)	(0.1679)		(0.4753)	(0.3191)
Financial	−0.0989	0.4839***	4	0.6892***	−0.2053***	−0.0662	0.4586***	3	0.8851***	−0.4265**
	(0.1092)	(0.1649)		(0.2492)	(0.0907)	(0.1122)	(0.1593)		(0.3185)	(0.1647)
Health care	0.7675***	−0.0298**	2	−0.1073***	0.0775***	0.7764***	−0.0237**	4	−0.0398**	0.0160***
	(0.0662)	(0.0152)		(0.0398)	(0.0268)	(0.0656)	(0.0102)		(0.0159)	(0.0058)
Industrial	0.5502***	−0.0224*	4	−0.0363**	0.0139**	0.5587***	−0.0285*	2	−0.0901**	0.0615**
	(0.0909)	(0.0121)		(0.0182)	(0.0066)	(0.0904)	(0.0166)		(0.0441)	(0.0283)
Information technology	0.8450***	−0.0472	2	−0.1575**	0.1103**	0.8182***	−0.0330**	4	−0.0622**	0.0291***
	(0.0748)	(0.0298)		(0.0778)	(0.0523)	(0.0709)	(0.0156)		(0.0245)	(0.0093)
Material	0.6747**	0.0284**	4	0.0483***	−0.0198***	0.6219***	−0.0254**	4	−0.0432***	0.0177***
	(0.0938)	(0.0109)		(0.0174)	(0.0068)	(0.0881)	(0.0103)		(0.0160)	(0.0059)
Real estate	0.8850***	0.0088*	2	0.0234*	−0.0146*	0.8902***	−0.0039	3	−0.0104*	0.0064**
	(0.0552)	(0.0048)		(0.0126)	(0.0081)	(0.0499)	(0.0030)		(0.0059)	(0.0030)
Utility	0.5321***	−0.0208	2	−0.0844**	0.0636**	0.5584***	0.0243*	4	0.0394*	−0.0150*
	(0.0937)	(0.0159)		(0.0419)	(0.0269)	(0.0884)	(0.0132)		(0.0211)	(0.0080)

Note(s): This table reports the ADL-MIDAS estimation results for the effect of climate risk on corporate profits without including control variables (e.g., technological innovations). For parsimony, the ADL-MIDAS model is estimated with a polynomial degree (PLD/Almon) of 2, or 3 when the lag length of 2 is found to be inefficient. The effect of each explanatory variable is obtained by summing the coefficients of the two polynomial degrees (PLD01 and PLD02), as determined using a Wald test. The lag length used corresponds to the optimal lag for the independent variable. Values in parentheses are standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively explains additional variation in corporate profits beyond the direct effects of climate risk. Table 3 reports the results for physical climate risk (PCR), while Table 4 reports the results for transition climate risk (TCR). The inclusion of green innovation generally reduces the magnitude of the negative coefficients for both PCR and TCR in several sectors. For example, in Communication Services and Consumer Discretionary, the negative effects of PCR persist, but positive and significant coefficients on green innovation indicate that sectoral technological progress contributes positively to profitability (Table 3). Similarly, in Energy and Financials, the sensitivity to TCR declines when controlling for green innovation, suggesting that technological progress accounts for part of the variation in profits that might otherwise be attributed solely to climate risk (Table 4).

The partial distributed lag (PDL) results show that both climate risk and green innovation effects unfold over two to four quarters, reflecting gradual responses to shocks and innovation adoption. This temporal dimension, observed in sectors such as Health Care, Utilities, and Information Technology, is consistent with prior findings (Faccini *et al.*, 2021; Colacito *et al.*, 2018) that climate and adaptation effects materialize gradually over time (Tables 3 and 4). Overall, the results indicate that climate risk remains a statistically and economically significant determinant of sectoral profits. Including green innovation as a control improves model performance and provides a clearer understanding of sector-specific dynamics. These findings highlight the importance of accounting for technological progress when evaluating the economic

Table 3. Results for sectoral corporate profits and physical climate risk nexus with the role of green innovation

	$Profit_{t-1}$	$Crisk_t$	$Tech_t$	Lag	PDL01	PDL02
Communication service	0.3792*** (0.1069)	−1.1356*** (0.2021)	0.0002*** (5.269e−05)	3	−0.4468*** (0.1208)	0.2448*** (0.0605)
Consumer discretionary	0.4817*** (0.0977)	−0.1020* (0.0599)	3.979e−05*** (1.337e−05)	3	−0.0647* (0.0347)	0.0339* (0.0186)
Consumer staple	0.4130*** (0.1001)	−0.0167 (0.0595)	5.532e−05*** (1.257e−05)	2	−0.1137** (0.0467)	0.0815*** (0.0318)
Energy	0.1475 (0.1106)	0.1316 (0.8975)	−0.0002** (0.0001)	2	−1.1856* (0.6859)	0.8347* (0.4677)
Financial	−0.0990 (0.1099)	1.6795*** (0.5154)	−3.398e−06 (0.0001)	4	0.6897*** (0.2512)	−0.2052** (0.0913)
Health care	0.0897 (0.1080)	−0.1134*** (0.0386)	8.900e−05*** (1.244e−05)	2	−0.0885*** (0.0313)	0.0586*** (0.0211)
Industrial	0.3536*** (0.1027)	0.0579 (0.0373	3.067e−05*** (8.943e−06)	4	−0.0389** (0.0171)	0.0132** (0.0062)
Information technology	0.2725** (0.1235)	−0.3350*** (0.0867)	0.0001*** (2.462e−05)	2	−0.1176* (0.0671)	0.0727 (0.0454)
Material	0.4935*** (0.1045)	0.0191 (0.0346)	2.841e−05*** (8.706e−06)	4	0.0405** (0.0166)	−0.0178*** (0.0065)
Real estate	0.7250*** (0.0771)	0.0095 (0.0169)	1.020e−05*** (3.577e−06)	2	0.0214* (0.0121)	−0.0132* (0.0078)
Utility	0.2251** (0.1094)	0.0067 (0.0430)	3.174e−05*** (7.114e−06)	2	−0.0843** (0.0380)	0.0613** (0.0244)

Note(s): This table reports the ADL-MIDAS estimation results for the role of green innovation as an additional predictor in the effect of physical climate risk on corporate profits. For parsimony, the ADL-MIDAS model is estimated with a polynomial degree (PLD/Almon) of 2, or 3 when the lag length of 2 is found to be inefficient. The effect of each explanatory variable is obtained by summing the coefficients of the two polynomial degrees (PLD01 and PLD02), as determined using a Wald test. The lag length used corresponds to the optimal lag for the independent variable. Values in parentheses are standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Table 4. Results for sectoral corporate profits and transition climate risk nexus with the role of green innovation

	$\boldsymbol{Profit_{t-1}}$	$\boldsymbol{Crisk_t}$	$\boldsymbol{Tech_t}$	Lag	PDL01	PDL02
Communication service	0.3741***	−0.4577**	0.0002***	4	0.1699**	−0.0593**
	(0.1175)	(0.1939)	(5.731e−05)		(0.0716)	(0.0259)
Consumer discretionary	0.4516***	−0.0878	4.183e−05***	3	−0.0557**	0.0271**
	(0.0971)	(0.0535)	(1.290e−05)		(0.0255)	(0.0127)
Consumer staple	0.4548***	0.0678	5.001e−05***	4	−0.0381**	0.0141**
	(0.1023)	(0.0409)	(1.264e−05)		(0.0173)	(0.0063)
Energy	0.1515	2.4453***	−0.0002	2	1.2343**	−0.7770**
	(0.1071)	(0.6257)	(0.0001)		(0.4701)	(0.3158)
Financial	−0.0672	1.8363***	4.931e−05	3	0.8863***	−0.4270**
	(0.1127)	(0.5568)	(0.0001)		(0.3201)	(0.1656)
Health care	0.0928	−0.0576**	8.846e−05***	4	−0.0265**	0.0112**
	(0.1080)	(0.0274)	(1.231e−05)		(0.0125)	(0.0046)
Industrial	0.3471***	0.0540	2.924e−05***	4	−0.0405***	0.0164***
	(0.1010)	(0.0361)	(8.520e−06)		(0.0142)	(0.0057)
Information technology	0.2313*	−0.2934***	0.0001***	4	−0.0454*	0.0204**
	(0.1221)	(0.0688)	(2.386e−05)		(0.0252)	(0.0100)
Material	0.4650***	−0.0484	2.402e−05***	4	−0.0350**	0.0146**
	(0.1016)	(0.0334)	(8.635e−06)		(0.0156)	(0.0057)
Real estate	0.7502***	−0.0051	1.055e−05***	4	0.0113**	−0.0043*
	(0.0735)	(0.0115)	(3.559e−06)		(0.0054)	(0.0022)
Utility	0.2384**	0.1293***	3.608e−05***	2	0.0448*	−0.0311*
	(0.1013)	(0.0354)	(7.030e−06)		(0.0234)	(0.0162)

Note(s): This table reports the ADL-MIDAS estimation results for the role of green innovation as an additional predictor in the effect of transition climate risk on corporate profits. For parsimony, the ADL-MIDAS model is estimated with a polynomial degree (PLD/Almon) of 2, or 3 when the lag length of 2 is found to be inefficient. The effect of each explanatory variable is obtained by summing the coefficients of the two polynomial degrees (PLD01 and PLD02), as determined using a Wald test. The lag length used corresponds to the optimal lag for the independent variable. Values in parentheses are standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

impacts of climate risks. The next step is to assess whether incorporating climate risk and green innovation enhances forecast accuracy, thereby demonstrating the practical utility of the ADL-MIDAS framework for applied economic analyses under climate uncertainty.

4.3 Forecast performance evaluation: ADL-MIDAS vs AR models

Tables 5 and 6 present the forecast evaluation using the Campbell–Thompson (C–T) test, comparing ADL-MIDAS models against a simple first-order autoregressive (AR(1)) benchmark. Table 5 reports the results without controlling for green innovation. The results show that climate risk variables, both physical (PCR) and transition (TCR), have significant predictive power for corporate profitability across sectors and forecast horizons. ADL-MIDAS models consistently outperform the AR benchmark, particularly at shorter horizons, highlighting the value of high-frequency climate data in near-term profit prediction. Sectors such as Consumer Discretionary, Financials, and Information Technology show the largest forecast gains (Table 5), indicating that transition risk carries substantial informational content beyond standard time series dynamics.

When green innovation is included as a control variable (Table 6), forecast performance improves further across all horizons. The gains are particularly pronounced in Communication Services, Health Care, and Information Technology, where out-of-sample C–T values remain high even at longer horizons (Table 6). This suggests that accounting for sectoral technological progress enhances the predictive accuracy of climate risk models by capturing additional,

Table 5. Campbell–thompson (C-T) test results for in-sample and out-of-sample forecasts: ADL-MIDAS without green innovation versus AR benchmark

	ADL-MIDAS (PCR) vs AR				ADL-MIDAS (TCR) vs AR			
	In-sample	Out-of-sample h = 4	h = 8	h = 12	In-sample	Out-of-sample h = 4	h = 8	h = 12
Communication service	0.1004	0.0516	−0.0074	0.3372	0.0005	0.0236	0.0262	0.3594
Consumer discretionary	0.2454	0.2023	0.1917	0.2235	0.3663	0.3566	0.3499	0.3754
Consumer staple	−0.0514	−0.0454	0.0038	0.1518	0.1327	0.1323	0.1514	0.2775
Energy	0.0096	0.0087	0.0929	0.0559	0.0765	0.0677	0.1357	0.1004
Financial	0.0848	0.0771	0.1091	0.1216	0.1017	0.1020	0.1026	0.1152
Health care	0.0738	0.0906	0.0890	0.1085	0.1753	0.0428	0.0307	0.0514
Industrial	0.1370	0.0779	0.1504	0.1442	0.1771	0.1147	0.1645	0.1584
Information technology	0.3322	0.3186	0.2863	0.3998	0.1844	0.1511	0.2092	0.3350
Material	0.1265	0.0982	0.0901	0.2830	0.2543	0.2262	0.2240	0.3885
Real estate	0.9793	0.9797	0.9816	0.9826	0.9754	0.9761	0.9787	0.9799
Utility	−4.8012	−4.0907	−3.8912	−3.6522	0.1121	0.1013	0.2213	0.2220

Note(s): The C–T test results are based on the forecast performance comparison of the ADL-MIDAS-based predictive model as against the AR process. Hypothetically, a positive C-T statistic or value implies that the ADL-MIDAS based predictive model outperforms the AR process and the reverse holds if the statistic is negative

economically relevant variation in profits. For climate-sensitive sectors such as Energy, Utilities, and Materials, the inclusion of green innovation significantly reduces forecast errors (Table 6), reflecting the importance of incorporating technological controls when anticipating firm-level responses to climate shocks.

From an applied economics perspective, these results imply that investors, managers, and policymakers can improve decision-making by jointly monitoring climate risk exposures and sectoral technological progress. Forecasting models that integrate both elements capture more of the additional variation relevant for forecasting performance in profits, particularly for vulnerable sectors. Even for sectors such as Real Estate and Consumer Staples, which show strong predictive performance without green innovation, the inclusion of technology controls refines forecasts (Tables 5 and 6). The results demonstrate that including sectoral technological progress as a control variable enhances the practical value of climate risk forecasts, providing a robust framework for applied economic and strategic analyses under climate uncertainty.

4.4 Forecast performance evaluation: unrestricted vs restricted ADL-MIDAS

Table 7 compares the unrestricted ADL-MIDAS model, which includes green innovation as a control, with the restricted specification excluding it. Across nearly all sectors and forecast horizons, the unrestricted model achieves higher in-sample and out-of-sample accuracy. Gains are most pronounced for PCR, with Communication Services, Health Care, and Information Technology recording C–T statistics above 0.70 across horizons. For instance, in Health Care, out-of-sample C–T rises from 0.7113 (h = 4) to 0.7296 (h = 12), reflecting improved tracking of long-term profit dynamics. Under TCR, the unrestricted model also outperforms, with Information Technology maintaining high C–T values (0.7355 at h = 8, 0.6843 at h = 12). Sectoral variation is evident: Energy, Utilities, and Financials show smaller improvements, likely due to slower innovation adoption or structural constraints, while innovation-intensive sectors—Information Technology, Health Care, and Real Estate—benefit most. These results indicate that including green innovation as a control enhances the practical value of climate risk forecasts,

Table 6. Campbell–thompson (C-T) test results for in-sample and out-of-sample forecasts: ADL-MIDAS with green innovation versus AR benchmark

	ADL-MIDAS (PCR) vs AR				ADL-MIDAS (TCR) vs AR			
	In-sample	Out-of-Sample h = 4	h = 8	h = 12	In-sample	Out-of-sample h = 4	h = 8	h = 12
Communication service	0.6678	0.7145	0.7337	0.8248	0.6224	0.6735	0.6952	0.7995
Consumer discretionary	0.5232	0.5205	0.4693	0.4902	0.5699	0.5512	0.4926	0.5125
Consumer staple	0.6291	0.6029	0.5790	0.6416	0.6318	0.5893	0.5250	0.5956
Energy	0.0366	0.0402	0.1477	0.1128	0.0881	0.0890	0.1900	0.1569
Financial	0.0852	0.0773	0.1091	0.1216	0.0932	0.0984	0.1050	0.1176
Health care	0.7336	0.7419	0.7537	0.7590	0.7487	0.7462	0.7569	0.7621
Industrial	0.5061	0.4924	0.3874	0.3829	0.5584	0.5385	0.4327	0.4285
Information technology	0.7759	0.7754	0.7504	0.7901	0.7749	0.7756	0.7589	0.7972
Material	0.4217	0.4185	0.4020	0.5288	0.4773	0.4664	0.4291	0.5501
Real estate	0.9903	0.9911	0.9920	0.9924	0.9901	0.9902	0.9913	0.9918
Utility	−2.6369	−2.1915	−2.2121	−2.1011	−1.7606	−1.4225	−1.6233	−1.3344

Note(s): The C–T test results are based on the forecast performance comparison of the unrestricted ADL-MIDAS-based predictive model as against the AR process. Hypothetically, a positive C-T statistic or value implies that the unrestricted ADL-MIDAS based predictive model outperforms the AR process and the reverse holds if the statistic is negative

Table 7. Campbell–thompson (C-T) test results for in-sample and out-of-sample forecasts: unrestricted ADL-MIDAS versus restricted ADL-MIDAS

	ADL-MIDAS (PCR + GREEN) vs ADL-MIDAS (PCR)				ADL-MIDAS (TCR + GREEN) vs ADL-MIDAS (TCR)			
	In-sample	Out-of-sample h = 4	H = 8	H = 12	In-sample	Out-of-sample h = 4	H = 8	H = 12
Communication service	0.6307	0.6990	0.7357	0.8566	0.6676	0.7076	0.7266	0.7211
Consumer discretionary	0.3682	0.3989	0.3434	0.3841	0.2476	0.2547	0.1837	0.1772
Consumer staple	0.6473	0.6202	0.5774	0.5447	0.5724	0.5423	0.5039	0.4193
Energy	0.0274	0.0317	0.0603	0.0603	−0.0429	−0.0294	0.0138	0.2421
Financial	0.0004	0.0002	−0.0001	−0.0005	−0.0183	−0.0275	0.0072	0.0075
Health care	0.7123	0.7161	0.7296	0.7113	0.6769	0.7303	0.7459	0.7687
Industrial	0.4278	0.4495	0.2789	0.2869	0.3998	0.4267	0.2667	0.2512
Information technology	0.6645	0.6704	0.6502	0.6502	0.7253	0.7355	0.6843	0.6324
Material	0.3379	0.3552	0.3428	0.3410	0.2244	0.2485	0.2294	0.2156
Real estate	0.5339	0.5651	0.5673	0.5671	0.6081	0.6306	0.6250	0.6050
Utility	0.3730	0.3710	0.3731	0.3706	0.5334	0.5331	0.3553	0.3555

Note(s): The C–T test results are based on the forecast performance comparison of the unrestricted ADL-MIDAS-based predictive model as against the restricted ADL-MIDAS-based predictive model. Hypothetically, a positive C-T statistic or value implies that the unrestricted ADL-MIDAS based predictive model outperforms the restricted ADL-MIDAS-based predictive model and the reverse holds if the statistic is negative

particularly in fast-innovating sectors, with implications for investor decision-making and policy targeting R&D and green adaptation strategies.

4.5 Robustness check

To evaluate the robustness of forecasting performance, the Clark and West (C–W) test was applied to assess whether the AR benchmark forecasts as well as or better than the ADL-MIDAS models. Comparing restricted ADL-MIDAS models (without green innovation) to the AR benchmark (Table 8) shows clear, statistically significant outperformance across most sectors and horizons (h = 4, 8, 12). Gains are strongest in Consumer Discretionary, Consumer Staples, Information Technology, and Real Estate, with t-statistics exceeding the 1% significance level. Sectors such as Energy and Financials show moderate improvements, while Utilities exhibit no significant advantage.

Including green innovation (Table 9) further improves forecast performance. Unrestricted ADL-MIDAS models dominate the AR benchmark across most sectors, especially Health Care, Communication Services, and Materials. Health Care shows t-statistics above 8 across all horizons, while Communication Services and Consumer Staples maintain consistently significant improvements.

Direct comparison of unrestricted and restricted ADL-MIDAS models (Table 10) confirms that including green innovation enhances predictive accuracy. Real Estate, Information Technology, Consumer Staples, and Health Care show significant gains across horizons. Cyclical sectors such as Energy and Industrials also benefit moderately, whereas Utilities remain largely unchanged. Financials display weaker differences, reflecting sector-specific dynamics.

These robustness checks indicate that ADL-MIDAS models, particularly in their unrestricted form with green innovation as a control, provide empirically superior forecasts of sectoral corporate profits under climate risk. The consistent significance across sectors and horizons demonstrates the reliability of the models for applied economic analyses, investment decision-making, and risk monitoring and scenario analysis in the context of climate transition.

Table 8. Clark and west (C-W) test results for in-sample and out-of-sample forecasts: ADL-MIDAS without green innovation versus AR benchmark

	ADL-MIDAS (PCR) vs AR				ADL-MIDAS (TCR) vs AR			
		Out-of-sample				Out-of-sample		
	In-sample	h = 4	h = 8	h = 12	In-sample	h = 4	h = 8	h = 12
Communication service	3.0164***	2.1952***	0.8963	0.8960	0.5772	1.1790	1.2969*	1.2969*
Consumer discretionary	5.1115***	4.7343***	4.9786***	4.9788***	4.8856***	4.9463***	5.0533***	5.0535***
Consumer staple	2.5733***	2.6224***	2.8472***	2.8470***	3.7651***	3.8112***	4.0871***	4.0870***
Energy	1.4398*	1.4679*	2.0515***	2.0510***	2.3858***	2.3127***	2.4776***	2.4779***
Financial	2.5275***	2.5854***	2.6853***	2.6851***	2.2205***	2.2916***	2.3367***	2.3360***
Health care	4.0604***	4.2328***	4.2486***	4.2485***	3.6853***	2.1996***	2.1136***	2.1140***
Industrial	4.1417***	3.4894***	3.5091***	3.5090***	4.0298***	3.4823***	3.9224***	3.9222***
Information technology	8.1263***	7.8829***	7.7260***	7.7270***	5.3707***	5.0284***	4.4867***	4.4865***
Material	3.5664***	3.5731***	3.6343***	3.6342***	5.0079***	4.9753***	5.0397***	5.0335***
Real estate	10.6043***	11.0586***	11.2924***	11.2921***	10.5536***	11.0143***	11.3121***	11.3123***
Utility	0.9924	0.9612	0.9791	0.8761	0.8935	0.8270	0.9360	0.8893

Note(s): The C-W test *t*-statistic is based on the critical values of 1.28, 1.64, and 2.00 for 10%, 5 and 1% levels of significance, respectively

Table 9. Clark and west (C-W) test results for in-sample and out-of-sample forecasts: ADL-MIDAS with green innovation versus AR benchmark

	ADL-MIDAS (PCR) vs AR				ADL-MIDAS (TCR) vs AR			
		Out-of-Sample				Out-of-sample		
	In-sample	h = 4	h = 8	h = 12	In-sample	h = 4	h = 8	h = 12
Communication service	4.3683***	4.9262***	5.3549***	5.3549***	5.7201***	6.1368***	6.6833***	6.6843***
Consumer discretionary	6.8740***	7.0426***	6.9095***	6.9099***	7.1576***	7.1757***	6.9297***	6.9291***
Consumer staple	6.3566***	6.2277***	6.2767***	6.2766***	6.6701***	6.4626***	6.3399***	6.3400***
Energy	2.1845***	2.4563***	2.6994***	2.6990***	2.5631***	2.7194***	2.9027***	2.9031***
Financial	2.5396***	2.5933***	2.6910***	2.6900***	2.1179***	2.2544***	2.3427***	2.3422***
Health care	8.7418***	8.8416***	9.4602***	9.4672***	8.2500***	8.7819***	9.4170***	9.4177***
Industrial	6.8169***	6.8304***	6.4603***	6.4660***	6.5769***	6.5172***	6.3781***	6.3780***
Information technology	8.4641***	8.6477***	8.8420***	8.8421***	8.3975***	8.5585***	8.6006***	8.6002***
Material	6.0182***	6.0046***	5.9545***	5.9546***	6.1734***	6.5100***	6.4132***	6.1734***
Real estate	11.5255**	11.9817***	12.1692***	12.1697***	11.5939***	11.9398***	12.0947***	2.0945***
Utility	1.0592	1.0581	1.0595	1.0758	0.4050	0.4058	0.4835	0.4857

Note(s): The C-W test *t*-statistic is based on the critical values of 1.28, 1.64, and 2.00 for 10%, 5 and 1% levels of significance, respectively

Table 10. Clark and west (C-W) test results for in-sample and out-of-sample forecasts: unrestricted ADL-MIDAS versus restricted ADL-MIDAS

	ADL-MIDAS (PCR + GREEN) vs ADL-MIDAS (PCR)				ADL-MIDAS (TCR + GREEN) vs ADL-MIDAS (TCR)			
		Out-of-sample				Out-of-sample		
	In-sample	h = 4	H = 8	H = 12	In-sample	h = 4	H = 8	H = 12
Communication service	3.8142***	4.4483***	4.7489***	4.7488***	6.3147***	6.7469***	7.2223***	7.2222***
Consumer discretionary	5.9018***	6.2098***	5.8463***	5.8466***	5.2331***	5.2671***	4.4450***	4.4451***
Consumer staple	7.5133***	7.2814***	7.1610***	7.1600***	6.4322***	6.0957***	5.6659***	5.6666***
Energy	2.6904***	2.8920***	3.4603***	3.4600***	2.5657***	2.8600***	3.5096***	3.5559***
Financial	0.6046	0.3236	−0.0092	−0.0096	−0.5847	−0.1211	0.4143	0.4141
Health care	8.7418***	9.1418***	9.7678***	9.7666**	7.4564***	7.0984***	7.6602***	7.6606***
Industrial	6.3940***	6.9216***	4.7852***	4.7855***	6.4201***	7.0203***	5.6753***	5.6757***
Information technology	7.4573***	7.6951***	8.0622***	8.0620***	8.4448***	8.9751***	8.8705***	8.8700***
Material	5.1081***	5.5592***	5.6899***	5.6990***	5.1214***	5.3986***	5.0289***	5.0284***
Real estate	10.0197***	10.5185***	10.8648***	10.8649***	8.2639***	8.6939***	8.7129***	8.7130***
Utility	1.0763	1.0732	1.0735	1.0803	0.3943	0.3937	0.3950	0.3895

Note(s): The C-W test *t*-statistic is based on the critical values of 1.28, 1.64 and 2.00 for 10%, 5 and 1% levels of significance, respectively

5. Conclusions

This study examines the predictive relationship between physical and transition climate risks and US sectoral corporate profitability within a mixed-frequency framework. Using ADL-MIDAS models, the findings indicate that climate risk measures contain significant predictive information for sectoral profits, with notable heterogeneity across industries. Incorporating green innovation improves forecast accuracy across most sectors and horizons, particularly in innovation-intensive industries. We show results that suggests that integrating climate risk indicators with measures of technological progress enhances the performance of predictive models, thereby improving the monitoring of sectoral exposure to climate-related risks. From a practical perspective, the results are relevant for investors, risk managers, and policymakers interested in forecasting and tracking climate-related financial risks. Rather than implying specific policy outcomes, the analysis highlights the value of combining climate and technological indicators in forward-looking risk assessment frameworks. Future research may extend this approach using firm-level data, alternative innovation measures, and cross-country comparisons.

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Further reading

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