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Climate and Green Technological Shocks in the U.S. Energy and Financial Sectors: Insights From Mixed-Frequency Profitability Analysis

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This study examines how climate and green technological shocks influence profitability in the U.S. energy and financial sectors. Using a mixed-frequency dataset (2000Q1–2024Q1), we combine daily climate risk indices with quarterly sectoral profits and green patent activity within an ADL-MIDAS framework. Results show that both physical and transition climate risks significantly predict profits, with stronger effects when green innovation is included. Forecast evaluations using the Clark–West test confirms superior predictive performance of green-augmented models. The findings highlight the joint importance of climate resilience and technological progress for sectoral profitability and policy design.

I. Introduction

The economic and operational impacts of climate change are increasingly recognized as critical determinants of corporate profitability. Climate-related shocks ranging from extreme weather events to persistent temperature anomalies can disrupt energy production, financial operations, and broader economic activity, leading to asset depreciation, supply chain interruptions, and financial instability (Ginglinger & Moreau, 2019; Kling et al., 2021; Pankratz et al., 2019). Evidence shows that physical climate risks negatively affect firm earnings, volatility, and profitability across sectors (Addoum et al., 2023; Fuss, 2016; Huang et al., 2018). The energy and financial sectors are particularly sensitive to such shocks. The energy sector is directly exposed to physical and transition risks through regulatory pressures, carbon pricing, and operational disruptions. Financial institutions, in turn, transmit climate-related risks indirectly via asset portfolios, credit exposures, and market valuation effects, shaping the resilience of the broader economy. By focusing on these two interlinked sectors, this study captures both the production and systemic financial dimensions of climate exposure, offering insights that are highly relevant for investors, policymakers, and risk managers.

While prior research has documented the adverse effects of climate risk on firm performance, most studies tend to treat firms as passive recipients of climate shocks and pay limited attention to adaptive mechanisms such as green innovation. For instance, Addoum et al. (2023) show that temperature shocks significantly reduce corporate earnings across industries, but their analysis does not account for technological adaptation. Similarly, Ginglinger and Moreau (2019) demonstrate that carbon risk exposure influences firms' cost of capital, while Kling et al. (2021) highlight how climate transition risk transmits through financial markets, both without considering the mitigating role of innovation. More recently, Liu (2024) finds that green innovation enhances firm performance and mitigates environmental risks, suggesting that technological adaptation can offset some of the negative profitability effects of climate shocks. However, sectoral heterogeneity and the predictive relevance of climate risk across production and financial sectors remain underexplored. This study addresses these gaps by focusing on the energy and financial sectors and assessing whether incorporating green innovation improves forecast accuracy under climate uncertainty.

At the same time, technological progress, particularly green innovation, can mitigate climate risk impacts by improving adaptive capacity and operational efficiency (Wang et al., 2018). Firms investing in climate-resilient technologies may reduce the frequency and severity of losses, enhance investor confidence, and seize growth opportunities in a low-carbon transition. Motivated by this perspective,

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we examine whether incorporating sectoral green innovation improves the predictive understanding of climate risk effects on profitability in the energy and financial sectors. Methodologically, we rely on a mixed-frequency econometric framework that allows high-frequency climate information to inform lower-frequency profitability dynamics, thereby capturing both immediate shocks and persistent adjustment effects.

This study contributes in three ways. First, it provides a sectorally focused analysis linking climate risks to profitability, emphasizing energy and financial sectors due to their pivotal role in production and financial intermediation. Second, it evaluates the moderating role of green innovation as a control variable, highlighting its capacity to buffer against climate shocks. Third, it demonstrates the practical utility of mixed-frequency modelling for short- and medium-term profit forecasts under climate uncertainty.

The remainder of the paper is organised as follows. Section II details the data and methodology employed in the analysis, Section III presents the empirical results and discussion, and Section IV concludes with policy implications and suggestions for future research.

II. Data and Methodology

This study employs a mixed-frequency dataset spanning 2000Q1–2024Q1, integrating quarterly U.S. sectoral corporate profits, daily climate risk indices, and quarterly green innovation data. While the full dataset covers all 11 GICS sectors, the analysis focuses on energy and the financial sectors. Energy is directly exposed to physical and transition climate risks, whereas the financial sector transmits these risks indirectly through credit, asset valuations, and market channels. Together, these sectors capture production- and finance-related dimensions of climate exposure, providing a tractable framework for analyzing the climate–profitability nexus. Corporate profit data, obtained from Bloomberg, include net profits after tax and combine financial statements, analyst forecasts, and standardized adjustments for comparability. Daily climate risks are derived from the climate risk index developed by Faccini et al. (2021). Physical climate risk captures temperature anomalies, extreme weather events, and natural disaster occurrences, while transition climate risk reflects climate policy uncertainty, regulatory announcements, and international climate negotiations. These high-frequency indicators are summarized via principal component analysis into physical climate risk (*PCR*) and transition climate risk (*TCR*). Sectoral green innovation is proxied using OECD ENV-TECH patent data, which provide a comprehensive set of patent statistics used to track innovation in environment-related technologies. Descriptive statistics presented in Table 1 show that energy exhibits high profit volatility, while the financial sector has higher, more stable earnings. Both climate risk indices display heavy tails, and green innovation is moderately distributed. These patterns justify using an ADL-MIDAS model to capture dynamic, asymmetric effects of climate risk and technological adaptation on corporate profitability.

Following Salisu and Ogbonna (2019), we adopt the Autoregressive Distributed Lag–Mixed Data Sampling (ADL-MIDAS) framework, which models both quarterly profit dynamics and daily climate risk effects. The general ADL-MIDAS specification is:

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

where $\mathrm{PROFIT}_{i,t}$ denotes net profits after tax for sector i at quarter t, and $\mathrm{CRISK}_{i,t}$ represents either *PCR* or *TCR* climate risk. The terms 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 a control variable in the ADL-MIDAS framework:

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

where $\mathrm{GREEN}_{i,t}$ is the quarterly green innovation index. This specification allows evaluation of climate risk's predictive power while controlling for sectoral technological progress. Forecast performance is compared against models excluding green innovation and a standard AR(1) benchmark.

$$PROFIT_t = \alpha + \lambda PROFIT_{t-1} + \varepsilon_t; \tag{3}$$

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

Forecast evaluation uses rolling-window out-of-sample predictions, with 75% of the sample used for estimation and 25% for forecasting over horizons of 1–12 quarters. Accuracy is assessed via the Clark–West (C-W, 2007) test. The C-W test provides statistical confirmation of improvements in forecast accuracy when green innovation is included.

III. Results

Table 2 presents the estimated effects of *PCR* and *TCR* on sectoral corporate profits for the energy and financial sectors, both without and with technological adaptation controls. In models excluding green innovation, the energy sector exhibits a significant negative response to *PCR*, with a lagged coefficient of −1.38. This finding implies that extreme weather events and temperature anomalies substantially depress profitability over multiple quarters, consistent with Addoum et al. (2023), who document that temperature shocks lower firm earnings across climate-exposed industries. *TCR*, by contrast, shows mixed effects—positive in the short term but negative in lag structures, reflecting adjustment costs to evolving regulations

Table 1. Descriptive statistics

Statistic	Energy	Financial sector	*PCR*	*TCR*	*GREEN*
Mean	669.72	1317.08	0.5359	0.6373	99.01
Max	2709.34	4223.57	5.3804	12.1436	137.73
Min	-6481.22	-2485.11	0.0001	0.0001	53.47
Std. Dev.	1059.12	1182.22	0.6220	0.8601	17.01
Skewness	-3.35	-0.27	2.31	3.46	-0.18
Kurtosis	22.81	3.77	10.33	23.24	2.69
Start Date	Mar-2000	Mar-2000	01/03/2000	01/03/2000	Mar-2000
End Date	Dec-2024	Dec-2024	12/31/2024	12/31/2024	Dec-2024
No. Obs.	100	100	7691	7691	100

Note: Max, Min, and Std. Dev. indicates maximum, minimum, and standard deviation, respectively, while No. Obs. represents the number of observations.

and market expectations. This aligns with evidence from Kling et al. (2021), who find that transition risks influence firm performance through changes in financing conditions and investor sentiment. The financial sector displays a different dynamic. Physical risk exerts a short-run positive effect, possibly due to portfolio rebalancing or reinsurance gains, while transition risk significantly affects profits through credit and valuation channels. These patterns mirror Ginglinger and Moreau (2019), who report that financial intermediaries often absorb or reprice climate exposures indirectly via asset markets.

Introducing green innovation as a control variable reshapes these relationships. For the energy sector, the adverse effect of *PCR* diminishes, and *TCR* coefficients turn more positive, indicating that technological adaptation helps offset climate-induced losses. This supports Liu (2024), who finds that green innovation enhances firms' resilience to environmental shocks. In the financial sector, the inclusion of innovation slightly strengthens the positive link between *PCR* and profitability, suggesting that technology-driven risk management tools and sustainable finance instruments improve adaptive capacity. Across both sectors, the significance of lagged PDL terms confirms the persistence and delayed transmission of climate impacts on profitability. In sum, these results suggest that climate sensitivity is sector-specific and that technological adaptation moderates climate-related profit shocks, particularly in the Energy sector.

Table 3 presents the C–W out-of-sample t-statistics, comparing the forecast performance of ADL-MIDAS models with and without green technological innovation against the AR(1) benchmark, as well as the unrestricted versus restricted ADL-MIDAS models. The results reveal several key patterns. For the energy sector, all ADL-MIDAS specifications outperform the AR benchmark across all horizons ($h = 4,\ 8,\ 12$), with t-statistics exceeding the 1% significance threshold in most cases. Incorporating green innovation further strengthens predictive performance, with the unrestricted models showing the largest gains, particularly at longer horizons (e.g., $PCR + GREEN\ t = 3.460\ at\ h = 12$). This indicates that technological adaptation meaningfully enhances the sector's ability to anticipate climate-driven profit fluctuations. Comparing unrestricted to restricted ADL-MIDAS models confirms that including green innovation significantly improves forecasts, suggesting that physical and transition climate risks are better captured when accounting for sectoral technological progress. For the financial sector, the ADL-MIDAS models also outperform the AR benchmark, though gains are more modest. The unrestricted *PCR* model shows negligible improvements over the restricted model, reflecting that financial sector profits are influenced by indirect climate channels and may respond less sensitively to sectoral green innovation. However, the *TCR*+*GREEN* model exhibits small but positive gains, consistent with financial firms' exposure to regulatory and transition uncertainties. The out-of-sample C–W results underscore that mixed-frequency ADL-MIDAS models, particularly when augmented with green technological indicators, provide robust forecasts of sectoral corporate profits under climate risk, with the effect being strongest in the energy sector.

IV. Conclusion

This study investigates how physical and transition climate risks affect U.S. energy and financial sector profits, highlighting the role of green technological innovation. Using mixed-frequency ADL-MIDAS models (2000Q1–2024Q1), daily climate risk indicators were combined with quarterly sectoral profits and green innovation measures to capture short- and long-term dynamics. Climate risks strongly predict sectoral profits, especially in energy, while including green innovation improves forecasts, showing that technology enhances resilience. Policy implications include promoting green R&D, carbon pricing with innovation incentives, renewable support, stronger climate disclosure, and sustainable finance to mitigate risks. Limitations include U.S.-focused data, patent-based innovation proxies, and a linear modelling framework. Future work could explore nonlinear climate shocks, firm-level responses, cross-country comparisons, or alternative innovation measures like green investments or technology adoption to better understand how innovation moderates climate risk impacts.

Table 2. Sectoral corporate profits and climate risk nexus – role of green innovation

Sector	Model / Variable	$\mathbf{PROFIT_{i,t-1}}$	$\mathbf{CRISK_{i,t}}$	$\mathbf{GREEN_{i,t}}$	Lag	PDL01	PDL02
Energy	Physical Climate Risk (No GREEN)	0.1977* (0.1100)	-0.4438* (0.2345)		2	-1.3809** (0.6928)	0.9370** (0.4743)
	Transition Climate Risk (No GREEN)	0.2045* (0.1057)	0.4929*** (0.1679)		2	1.3507*** (0.4753)	-0.8577*** (0.3191)
	Physical Climate Risk (With GREEN)	0.1475 (0.1106)	0.1316 (0.8975)	-0.0002** (0.0001)	2	-1.1856* (0.6859)	0.8347* (0.4677)
	Transition Climate Risk (With GREEN)	0.1515 (0.1071)	2.4453*** (0.6257)	-0.0002 (0.0001)	2	1.2343** (0.4701)	-0.7770** (0.3158)
Financial	Physical Climate Risk (No GREEN)	-0.0989 (0.1092)	0.4839*** (0.1649)		4	0.6892*** (0.2492)	-0.2053*** (0.0907)
	Transition Climate Risk (No GREEN)	-0.0662 (0.1122)	0.4586*** (0.1593)		3	0.8851*** (0.3185)	-0.4265** (0.1647)
	Physical Climate Risk (With GREEN)	-0.0990 (0.1099)	1.6795*** (0.5154)	-3.398e-06 (0.0001)	4	0.6897*** (0.2512)	-0.2052** (0.0913)
	Transition Climate Risk (With GREEN)	-0.0672 (0.1127)	1.8363*** (0.5568)	4.931e-05 (0.0001)	3	0.8863*** (0.3201)	-0.4270** (0.1656)

Notes: PDL01 and PDL02 denote the first and second polynomial distributed lag terms. Standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. “No GREEN” refers to models excluding green innovation; “With GREEN” includes green innovation as a control.

Table 3. Forecast Performance Evaluation [C-W test]

Sector	Model Comparison	In-sample	Out-of-sample		
			$\mathbf{h = 4}$	$\mathbf{h = 8}$	$\mathbf{h = 12}$
Energy	PCR vs AR	1.440*	1.468*	2.052***	2.051***
	TCR vs AR	2.386***	2.313***	2.478***	2.478***
	$PCR + GREEN$ vs AR	2.185***	2.456***	2.699***	2.699***
	$TCR+ GREEN$ vs AR	2.563***	2.719***	2.903***	2.903***
	$PCR+ GREEN$ vs PCR	2.690***	2.892***	3.460***	3.460***
	$TCR+ GREEN$ vs TCR	2.566***	2.860***	3.510***	3.556***
Financial	PCR vs AR	2.528***	2.585***	2.685***	2.685***
	TCR vs AR	2.221***	2.292***	2.337***	2.336***
	$PCR + GREEN$ vs AR	2.540***	2.593***	2.691***	2.690***
	$TCR+ GREEN$ vs AR	2.118***	2.254***	2.343***	2.342***
	$PCR+ GREEN$ vs PCR	0.605	0.324	-0.009	-0.010
	$TCR+ GREEN$ vs TCR	-0.585	-0.121	0.414	0.414

Note: Table 3 reports the C–W test statistics evaluating the forecast performance of ADL-MIDAS models, namely, physical climate risk (PCR), transition climate risk (TCR), and their technology-augmented versions, ($PCR + GREEN$, $TCR + GREEN$), against benchmark autoregressive (AR) models and restricted counterparts. Positive and significant values indicate superior predictive accuracy of the ADL-MIDAS model. Forecast horizons are $h = 4,\ 8,\ 12$ quarters. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

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