International Journal of Finance & Economics

WILEY

SPECIAL ISSUE ARTICLE OPEN ACCESS

Climate Change and Investors' Behaviour: Assessing a New Type of Systematic Risk

Natthinee Thampanya[1] | Junjie Wu[2]

[1]Oxford Brookes Business School, Oxford Brookes University, Oxford, UK | [2]Leeds Business School, Leeds Beckett University, Leeds, UK

Correspondence: Natthinee Thampanya (nthampanya@brookes.ac.uk)

Received: 30 September 2023 | **Revised:** 23 September 2024 | **Accepted:** 6 December 2024

Funding: The authors received no specific funding for this work.

Keywords: climate change | ESG score | investor behaviour | stock returns | systematic risk | temperature anomaly

ABSTRACT

This study explores how temperature anomalies, a novel form of systematic risk, affect financial markets, expanding the traditional understanding of market-wide risks. While climate change is becoming an important consideration, the extent to which temperature anomalies disrupt economic activities and influence stock returns is urgently needed to assess. Using data from 479 Thai companies (2010–2023), we apply linear and nonlinear autoregressive distributed lag (ARDL) models to examine the impact of temperature anomalies and investor sentiment on stock returns. Our findings reveal that (1) temperature anomalies significantly affect short-term stock returns, especially when prioritising sustainability and environmental, social, and governance (ESG) factors; (2) public awareness, measured by Google Search Volume Index (GSVI), has a complex, nonlinear impact on the stock market; (3) temperature anomalies act like traditional risk measures, influencing stock returns similarly to market volatility. The study highlights the growing importance of climate change in financial decision-making and offers insights into investor reactions to climate risks and economic sentiment. It emphasises the need to consider short-term market reactions to climate-related news and suggests that temperature anomalies could be viewed as a systematic risk in financial markets.

JEL Classification: F14, F15, F43, E31, Q41, Q43

1 | Introduction

Climate change, a defining challenge of this century, profoundly reshapes sociological, geopolitical, and financial dynamics (Dell, Jones, and Olken 2012). In the financial realm, climate-induced disruptions in production and consumption directly affect asset values and stock prices due to expected reductions in future cash flows and profitability. For example, extreme weather events can damage infrastructure and disrupt supply chains, leading to production losses and increased company costs. This, consequently, can negatively impact their stock prices and investment decisions (Hjort 2016; NGFS 2020).

As traditionally understood, systematic risk encompasses risks that affect an entire market or segment, such as economic recessions, interest rate changes, or geopolitical tensions (Fama and French 1993). However, the increasing recognition of climate change as a systemic risk has added a new dimension to this concept because temperature anomalies caused by climate change can be viewed as unexpected economic shocks that disrupt normal economic activities (Balvers, Du, and Zhao 2017; Bansal, Kiku, and Ochoa 2019; Nagar and Schoenfeld 2021), for example, higher temperatures can increase energy demand, leading to higher costs for businesses and consumers, which can, in turn, affect stock returns.

The concept of temperature anomalies as a systematic risk challenges the conventional wisdom that only traditional economic factors drive market-wide risks. Temperature anomalies, characterised by deviations from long-term climate norms, can lead to significant economic disruptions, influencing stock returns across various sectors (Addoum, Ng, and Ortiz-Bobea 2021). These anomalies are not isolated incidents but increasingly becoming a persistent and systemic feature of the global climate system, impacting asset values and investment decisions on a broad scale (Engle et al. 2020; Bolton and Kacperczyk 2021; El Ouadghiri et al. 2021).

Despite increasing relevance, there is a noticeable lack of studies addressing how investors react to temperature anomalies, a systematic risk affecting stock returns due to climate change. Temperature anomalies can have asymmetric and non-linear effects on economic activity and financial markets that are not fully captured, and examining temperature anomalies can specifically reveal these nuanced impacts (Tzouvanas et al. 2019). Moreover, previous research has predominantly focused on investigating the effects of climate and natural hazards in developed markets (Addoum, Ng, and Ortiz-Bobea 2020, 2021; Bolton and Kacperczyk 2021; Nagar and Schoenfeld 2021), while paying limited attention to emerging markets (Lucas and Mendes-Da-Silva 2018; Rao et al. 2021). However, temperature anomalies act as economic shocks, disrupting normal economic activities and potentially altering long-term growth trajectories (Kumari and Mahakud 2015), with more severe impacts observed in developing countries and climate-sensitive regions like Thailand.

To address this gap, we introduce and explore temperature anomalies as a novel form of systematic risk that mirrors the role of beta in the traditional Capital Asset Pricing Model (CAPM) but with distinct implications rooted in environmental and sustainability considerations. Specifically, building on prior work (Choi, Gao, and Jiang 2020; Engle et al. 2020) that focused on investor climate change awareness, we argue investors' choices may reflect their values and climate change commitment, potentially favouring sustainable investments (Hart and Dowell 2011; Yang, Wong, and Miao 2020). Thus, we assess if sustainability-focused companies (Green stocks) outperform less eco-friendly ones (NonGreen stocks). Furthermore, our analysis also includes the Google Search Volume Index (GSVI) as a sentiment variable concerning public awareness of the economic conditions (Choi, Gao, and Jiang 2020; Engle et al. 2020; El Ouadghiri et al. 2021).

We employ a dataset encompassing 479 listed companies in Thailand during 2010–2023. The selection of data sample is because tropical nations like Thailand are highly vulnerable to climate change.[1] Importantly, the stock exchange of Thailand (SET) is widely recognised as a key emerging market within the ASEAN region, making it an attractive investment destination for domestic and international investors.[2] Our analysis employs linear and nonlinear ARDL models to capture the complex dynamics between temperature anomalies, investor sentiment, and stock returns.

Our findings offer insights into the relationship between temperature anomalies and industry-level stock returns. While no significant correlation is observed between temperature anomalies and stock returns across the entire industry, the influence of this form of systematic risk becomes more apparent when viewed through an ESG lens. Specifically, *temperature anomalies have a notable short-term effect on Green stocks*. In contrast, *beta demonstrates statistical significance across all three data groups* (aggregate market level, Non-Green, and Green stocks). Interestingly, we find *a consistent negative relationship between beta and the impact of temperature anomalies on stock returns, suggesting that temperature anomalies may serve a role similar to the standard CAPM systematic risk measure (beta), particularly for sustainable firms*.

Using the NARDL approach, we find that temperature anomalies have a linear effect on the stock returns of Green companies. However, for Non-Green stocks, the impact of temperature anomalies is more pronounced under a nonlinear assumption. Additionally, adverse shocks related to public attention on economic conditions have a stronger effect on stock returns, indicating that a decrease in economic condition awareness leads to higher stock returns than an increase.

This research contributes significantly to the existing literature in several ways. First and foremost, we undertake a concurrent analysis of the effects of temperature anomalies (a novel form of systematic risk) and the conventional CAPM measure of systematic risk (beta) on stock returns. These dual examinations allow our findings to illuminate the increasing influence of temperature anomalies on financial markets.

Second, by uncovering the nonlinear nature of investor behaviour, the study contributes to the broader field of behavioural finance, offering a nuanced perspective on how psychological factors, such as sentiment and cognitive biases, influence financial decision-making in the context of ESG criteria. Third, we include alternative GSVI as a sentiment variable concerning public awareness of economic conditions. This insight is crucial for understanding market dynamics during periods of economic uncertainty. It suggests that traditional economic indicators may not fully capture market behaviour, as investor focus can shift in ways that influence asset prices in unexpected directions. This has implications for portfolio management and risk assessment, particularly in volatile markets.

Fourth, we evaluate how a company's commitment to ESG principles should influence investor behaviour regarding their attention to climate change issues. Our findings contribute to investor behaviour and risk perception and highlight that investors may have a more stable and predictable approach to pricing climate risks for companies with strong ESG credentials. In contrast, the more pronounced nonlinear impact on Non-Green stocks suggests that investors may only react significantly to climate risks when these risks reach a certain threshold, revealing potential behavioural biases such as underreacting to gradual risks but overreacting to severe anomalies.

Finally, and notably, when considering climate change risk factors, public awareness of climate change and temperature anomalies significantly impact Green stock returns in the short term, unlike the long-term results. The immediate and lagged effects tend to offset each other within a month. This insight suggests that the market quickly absorbs climate-related information in finance and economics, leading to temporary stock price adjustments. This highlights the importance of timing and the potential for short-term trading opportunities based on climate-related news for portfolio management. It also implies that long-term investors should look beyond short-term volatility when evaluating the impact of climate risks.

The remainder of the paper is structured as follows: Section 2 provides a literature review on climate change risk and stock returns to formulate hypotheses; Section 3 outlines the data and methodology; Section 4 presents the empirical findings and discussion; and finally, Section 5 concludes and deliberates research implications.

2 | Literature Review and Hypothesis Development

2.1 | Climate Change Risk: Additional Systematic Risk

Climate change risks can be broadly categorised into physical and transitional. Physical risks refer to the direct impacts of climate-related events on business operations, society, and supply chains. These include acute risks, such as extreme weather events (e.g., heatwaves, hurricanes, and floods), and chronic risks, such as rising sea levels, altered rainfall patterns, and increasing temperatures. Transitional risks involve the economic shifts associated with transitioning to a low-carbon economy, including the impact on fossil fuel sectors, company reputations, and technological adaptations in response to climate change.

Recent studies in corporate finance have begun examining how climate risks affect firm-level outcomes. Bolton and Kacperczyk (2021) explore the effect of carbon emissions on U.S. stock returns, finding that firms with higher emissions yield greater returns, particularly when accounting for variables like book-to-market ratios and company size. This suggests that investors demand compensation for bearing carbon emission risks. Addoum, Ng, and Ortiz-Bobea (2021) analyse the impact of extreme temperatures on corporate profitability across different industries in the U.S., revealing that temperature extremes influence earnings for over 40% of industries. This aligns with Amel-Zadeh's (2021) findings, highlighting businesses' concerns about physical risks affecting customer demand.

The impact of climate risk on asset pricing has received significant attention in recent years. Traditional asset pricing models, such as the CAPM, have focused on economic factors to explain systematic market risks. However, emerging research suggests that climate-related factors, particularly temperature anomalies, may be crucial in asset pricing. For example, Balvers, Du, and Zhao (2017) demonstrated that including temperature factors improves the explanation of cross-sectional variance in industry portfolios. This finding suggests that temperature anomalies may serve as an additional factor in asset pricing models, complementing the traditional beta in the CAPM. Bansal, Kiku, and Ochoa (2019) developed a temperature-adjusted long-run risk model, noting negative stock price elasticity to temperature risks. Their work provides a theoretical foundation for incorporating climate risk into asset pricing models, extending beyond the single-factor approach of the CAPM. Nagar and Schoenfeld (2021) further identified the 'weather premium' as a novel systematic risk that enhances the predictability of U.S. stock returns. This research suggests that temperature anomalies may act as a proxy for climate risk in asset pricing models, similar to how beta captures market risk in the CAPM.

The traditional CAPM posits that an asset's expected return is determined by its sensitivity to market risk, represented by beta. However, the growing body of evidence on climate risk suggests that this model may be incomplete in capturing all relevant systematic risks. Choi, Gao, and Jiang (2020) showed that abnormally high temperatures can drive retail investors to trade low-carbon stocks, suggesting a slow adjustment in market beliefs regarding climate change risks. This finding implies that temperature anomalies may contain information about systematic risk that is not fully captured by traditional market factors. Kumar, Xin, and Zhang (2019) observed that the market's delayed response to climate risks creates temporary trading opportunities. This further supports the idea that climate risk, particularly in temperature anomalies, represents an additional dimension of systematic risk not accounted for in the standard CAPM.

Given the evidence that temperature anomalies play a significant role in asset pricing and represent a form of systematic risk, we propose the following hypothesis:

Hypothesis 1. *Temperature anomalies act as a novel form of systematic risk—one that mirrors the role of beta in the traditional CAPM.*

2.2 | Investor Climate Sentiment

Traditional asset pricing models, grounded in the efficient market hypothesis, highlight the relationship between investor attention and stock prices. Two key theories in this context are Merton's 'investor recognition hypothesis' (1987) and Barber and Odean's 'price pressure hypothesis' (2008), which both suggest that stocks attracting investor attention often experience increased trading volumes and abnormal returns.

Empirical research supports this attention-driven price fluctuation. For example, Da, Engelberg, and Gao (2011) introduced using Google search data to directly measure investor attention, demonstrating that the GSVI effectively captures retail investors' focus. More recently, studies have leveraged GSVI and news media data to assess investor perceptions and concerns related to climate change risks (Engle et al. 2020; Faccini, Matin, and Skiadopoulos 2023; Ardia et al. 2022; Pástor, Stambaugh, and Taylor 2021).

Building on this, behavioural finance models argue that investor sentiment, coupled with limited attention, can lead to stock price misalignments such as underreactions and overreactions (De Long et al. 1990; Hirshleifer and Teoh 2003). Climate sentiment—investor attitudes toward climate-related risks—plays an increasingly important role in shaping market dynamics. Santi (2023) used sentiment analysis of StockTwits posts to show that positive climate sentiment can lead to the underperformance of carbon-intensive companies compared to low-emission stocks, reflecting an overreaction to climate risks followed by market corrections. Notably, major climate events, like the release of high-profile climate reports, trigger investor learning and subsequent corrections in mispricing.

Investor climate sentiment can create pricing inefficiencies, especially in stocks with high volatility or speculative characteristics. Baker and Wurgler (2006, 2007) note that strong investor sentiment can lead to mispricing, particularly in such contexts. Similarly, Anastasiou and Drakos (2021) found that tracking online search behaviour could help policymakers anticipate market reactions, offering new predictive tools. Tzomakas et al. (2023) further illustrate how increased crisis sentiment drives greater stock price volatility, highlighting the significance of sentiment-driven risks in asset pricing.

Given the rising attention to climate change risks and the role of investor sentiment, corporate sustainability becomes crucial in mitigating these risks—particularly for firms with weaker governance structures (Kim, Li, and Li 2014). Companies with robust Corporate Social Responsibility (CSR) practices tend to secure more favourable credit ratings and loan terms (Attig et al. 2013; Nandy and Lodh 2012), while higher levels of environmental activism are associated with increased transparency, which influences the credit channel (Lopatta, Buchholz, and Kaspereit 2016). Financial institutions are increasingly inclined to finance eco-friendly businesses due to consumer demand for sustainable products (Mason 2013).

The growing integration of ESG criteria into financial services across many countries further underscores the importance of sustainability in corporate strategy. By adopting sustainable practices, firms can improve performance and meet stringent environmental regulations (Albertini 2019). Firms with weaker environmental performance face heightened risks of regulatory penalties or stakeholder boycotts (Trapp 2014). Conversely, adopting a green strategy can help firms build a sustainable competitive advantage (Hart and Dowell 2011; Elijido-Ten and Clarkson 2019).

Investor behaviour increasingly reflects this sustainability focus. Sustainable investors, driven by environmental awareness, tend to adjust their portfolios by investing in companies with strong ESG profiles and divesting from less eco-friendly firms (El Ouadghiri et al. 2021). Even traditional investors are now more likely to prioritise sustainable stocks as public environmental concern grows. Evidence shows that firms with strong ESG performance experience lower return volatility and higher valuations (Khan, Serafeim, and Yoon 2016; Dutordoir, Strong, and Sun 2018; Giese et al. 2019).

Considering these dynamics, it is essential to consider whether investors' focus on climate change stems from rational considerations or a preference for responsible investing. The evidence suggests that environmental criteria influence investment decisions, especially during periods of heightened climate awareness. Given the systematic impact of investor climate sentiment and the mitigating role of corporate social responsibility, we propose the following hypothesis:

Hypothesis 2. *High-sustainability companies outperform low-sustainability companies when climate change awareness increases.*

3 | Data and Methodology

3.1 | Data and Descriptive Statistics

We used a monthly panel dataset spanning 2010–2023 with 479 Thai-listed companies. Stock returns were analysed by ESG responsibility and industry. Explanatory variables include CAPM beta, temperature anomaly (for climate risk; Venturini 2022), GSVI_climate, GSVI_sentiment, and unsystematic risk measures like EPS, market capitalisation, and PBV ratio. Data came primarily from Refinitiv, with temperature data from the World Bank Group's climate knowledge portal (2021b).

3.1.1 | Measuring People's Attention

We use GSVI from Google Trends Analytics, following prior research (Herrnstadt and Muehlegger 2014; Choi, Gao, and Jiang 2020; El Ouadghiri et al. 2021). These studies examined environmental concerns, global warming, and climate change using GSVI. Choi, Gao, and Jiang (2020) and El Ouadghiri et al. (2021) found positive links between climate change-related GSVI and sustainability index returns. Our approach expands data collection to include English and Thai languages.

Monthly search volumes of finance and economics terms in English and Thai measure sentiment on economic conditions (GSVI_sentiment).

3.1.2 | Measuring ESG Responsibility

Since 2015, SET has established the Thailand Sustainability Investment (THSI) list and SETTHSI index for high-performing ESG stocks. We examine subsets of SETTHSI-listed (Green stocks) and non-SETTHSI-listed (Non-green stocks), with 93 green and 386 non-green stocks.

Table 1 summarises key statistics. Green stocks show higher profitability but lower returns and higher beta than non-green stocks. The average market capitalisation is 30,277.47 billion THB, with 2.64 average PBV. Temperature increases average 0.30°C monthly, while climate change attention rises 12.4%. Sentiment concerning economic conditions increases 0.5% on average.

Table 2 shows correlations between variables and stock returns. Unsystematic risk factors (EPS, market capitalisation, and PBV) positively correlate with returns, while systematic risk factors (beta, GSVI_climate, GSVI_sentiment, and temperature anomaly) negatively correlate. Increasing climate change attention is associated with higher returns for both green and non-green stocks. Traditional and climate-related systematic risks show

TABLE 1 | Descriptive statistics.

	Rt_SET	Beta	EPS	GSVI_Climate	GSVI_Sentiment	Market_Cap	PBV	Temp
Mean	0.065	0.869	1.591	0.124	0.005	30,277.474	2.639	0.300
Median	0.000	0.830	0.330	0.000	0.003	3196.290	1.210	0.290
Maximum	927.500	24.880	189.670	8.083	0.297	1,613,808.000	3456.600	2.200
Minimum	−1.000	−3.250	0.000	−0.899	−0.231	27.650	−2091.970	−2.130
Std. dev.	4.745	0.541	4.986	0.845	0.096	103,497.361	63.290	0.737
Skewness	158.141	1.618	12.727	6.947	0.034	6.571	27.354	−0.290
Kurtosis	28,033.253	62.619	334.628	60.353	3.243	56.214	1983.098	3.757
Jarque-Bera	2,136,118,492,020.1	9,718,060.8	300,020,445.0	9,381,086.8	172.2	8,174,899.8	10,521,787,064.2	2465.1
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

	Rt_NonGreen	Beta	EPS	Market_Cap	PBV
Mean	0.064	0.827	1.327	12,013.008	2.764
Median	0.000	0.770	0.230	2255.010	1.140
Maximum	654.556	24.880	189.670	1,142,855.000	3456.600
Minimum	−1.000	−2.630	0.000	27.650	−2091.970
Std. dev.	3.674	0.555	4.957	53,141.010	72.103
Skewness	133.076	1.979	15.441	12.445	24.012
Kurtosis	21,476.904	72.764	436.789	192.421	1528.231
Jarque-Bera	970,325,080,934.5	10,302,690.2	396,416,513.3	76,882,335.5	4,809,897,202.3
Probability	0.000	0.000	0.000	0.000	0.000

	Rt_Green	Beta	EPS	Market_Cap	PBV
Mean	0.028	1.011	2.488	92,884.170	2.221
Median	0.000	0.980	0.790	19,058.070	1.450
Maximum	130.034	3.780	55.130	1,613,808.000	21.700
Minimum	−1.000	−3.250	0.000	238.000	0.000
Std. dev.	1.251	0.460	4.979	180,797.657	2.155
Skewness	85.066	0.111	4.405	3.398	2.934

(Continues)

TABLE 1 | (Continued)

	Rt_Green	Beta	EPS	Market_Cap	PBV
Kurtosis	8249.870	3.375	28.744	16.800	14.591
Jarque-Bera	41,807,623,833.8	116.9	456,076.4	145,251.0	103,966.3
Probability	0.000	0.000	0.000	0.000	0.000

similar relationships with returns across all sample groups, emphasising climate risk's importance in asset pricing. We conducted further linear and nonlinear ARDL analyses to investigate these relationships.

3.2 | ARDL Model

We investigated short-term and long-term connections between stock returns and various risks using Pesaran, Shin, and Smith's (2001) linear autoregressive distributed lag (ARDL) model. We then applied Shin, Yu, and Greenwood-Nimmo's (2014) nonlinear ARDL (NARDL) model to account for asymmetries in the relationships between stock returns, temperature anomalies, and sentiment factor (GSVI_sentiment). The NARDL model uses partial sum decomposition of explanatory variables, distinguishing between increases and decreases in temperature anomalies and GSVI_Sentiment and positive and negative changes in stock returns. The functional form of the econometric model is as follows:

$$\begin{aligned}\mathrm{RET}_{it} = f(&\mathrm{Beta}_{it}, \mathrm{EPS}_{it}, \mathrm{Market\ Cap}_{it}, \mathrm{PBV}_{it}, \mathrm{Temp}_{it},\\ &\mathrm{GSVI\_Climate}_{it}, \mathrm{GSVI\_Sentiment}_{it})\end{aligned} \tag{1}$$

It can be stated more formally as:

$$\begin{aligned}\mathrm{RET}_{it} = {} & \alpha_0 + \alpha_1 \mathrm{Beta}_{it} + \alpha_2 \mathrm{EPS}_{it} + \alpha_3 \mathrm{Market\ Cap}_{it}\\ & + \alpha_4 \mathrm{PBV}_{it} + \alpha_5 \mathrm{Temp}_{it} + \alpha_6 \mathrm{GSVI\_Climate}_{it}\\ & + \alpha_7 \mathrm{GSVI\_Sentiment}_{it} + \varepsilon_{it}\end{aligned} \tag{2}$$

where, RET_{it} is monthly stock returns, Beta_{it} refers to the CAPM beta, EPS_{it} is earnings per share, Market Cap_{it} is the market capitalisation, PBV_{it} is price-to-book ratio, Temp_{it} is temperature anomaly, GSVI_Climate is Google Search Volume Index for awareness of climate change, and GSVI_Sentiment is Google Search Volume Index for attention of economics condition. The $i = 1, 2 \ldots N$, $t = 1, 2 \ldots T$, here, N is the individual stock in all panels, T is the analytical periods in the months.

3.3 | Bounds Test for Cointegration

The assessment of the panel ARDL model using the bounds test method utilises the following equation, following the approach outlined by Aristei and Martelli (2014):

$$\begin{aligned}\Delta\mathrm{RET}_{it} = {} & \beta_1 + \sum_{i}^{k} a_{ij}\,\Delta\mathrm{RET}_{j,t-1} + \sum_{i=0}^{k} \beta_{ij}\,\Delta\mathrm{Beta}_{j,t-i} + \sum_{i=0}^{k} X_{ij}\,\Delta\mathrm{EPS}_{j,t-i}\\ & + \sum_{i=0}^{k} \delta_{ij}\,\Delta\mathrm{Market\ Cap}_{j,t-i} + \sum_{i=0}^{k} \partial_{ij}\,\Delta\mathrm{PBV}_{j,t-i}\\ & + \sum_{i=0}^{k} \gamma_{ij}\,\Delta\mathrm{Temp}_{j,t-i} + \sum_{i=0}^{k} \omega_{ij}\,\Delta\mathrm{GSVI\_Climate}_{j,t-i}\\ & + \sum_{i=0}^{k} \pi_{ij}\Delta\mathrm{GSVI\_Sentiment}_{j,t-i} + \emptyset_1 \mathrm{RET}_{j,t-i}\\ & + \emptyset_2 \mathrm{Beta}_{j,t-i} + \emptyset_3 \mathrm{EPS}_{j,t-i} + \emptyset_4 \mathrm{Market\ Cap}_{j,t-i}\\ & + \emptyset_5 \mathrm{PBV}_{j,t-i} + \emptyset_6 \mathrm{Temp}_{j,t-i} + \emptyset_7 \mathrm{GSVI\_Climate}_{j,t-i}\\ & + \emptyset_8 \mathrm{GSVI\_Sentiment}_{j,t-i} + \varepsilon_{it}\end{aligned} \tag{3}$$

TABLE 2 | Correlation matrices.

	Rt_SET	Beta	EPS	GSVI_Climate	GSVI_Sentiment	Market_Cap	PBV	Temp
Rt_SET	1.000	−0.021	0.014	−0.002	−0.004	0.038	0.002	−0.001
Beta	−0.021	1.000	−0.124	0.000	0.000	0.182	−0.004	−0.011
EPS	0.014	−0.124	1.000	0.000	−0.001	0.204	−0.003	0.002
GSVI_Climate	−0.002	0.000	0.000	1.000	−0.058	0.000	0.000	−0.039
GSVI_Sentiment	−0.004	0.000	−0.001	−0.058	1.000	0.000	−0.002	−0.008
Market_Cap	0.038	0.182	0.204	0.000	0.000	1.000	0.016	−0.002
PBV	0.002	−0.004	−0.003	0.000	−0.002	0.016	1.000	0.006
Temp	−0.001	−0.011	0.002	−0.039	−0.008	−0.002	0.006	1.000

	Rt_NonGreen	Beta	EPS	GSVI_ Climate	GSVI_ Sentiment	Market_Cap	PBV	Temp
Rt_NonGreen	1.000	−0.031	0.016	0.005	−0.001	0.034	0.003	−0.002
Beta	−0.031	1.000	−0.156	−0.001	0.000	0.118	−0.003	−0.006
EPS	0.016	−0.156	1.000	0.001	0.001	0.093	−0.003	0.010
GSVI_Climate	0.005	−0.001	0.001	1.000	−0.058	0.000	0.001	−0.040
GSVI_Sentiment	−0.001	0.000	0.001	−0.058	1.000	−0.001	0.000	−0.008
Market_Cap	0.034	0.118	0.093	0.000	−0.001	1.000	0.021	0.005
PBV	0.003	−0.003	−0.003	0.001	0.000	0.021	1.000	0.001
Temp	−0.002	−0.006	0.010	−0.040	−0.008	0.005	0.001	1.000

	Rt_Green	Beta	EPS	GSVI_Climate	GSVI_Sentiment	Market_Cap	PBV	Temp
Rt_Green	1.000	−0.009	0.012	0.002	0.006	0.040	0.044	−0.001
Beta	−0.009	1.000	−0.074	0.002	0.001	0.184	−0.177	0.012
EPS	0.012	−0.074	1.000	−0.001	0.000	0.425	0.028	−0.003
GSVI_Climate	0.002	0.002	−0.001	1.000	−0.058	−0.001	−0.004	−0.039
GSVI_Sentiment	0.006	0.001	0.000	−0.058	1.000	0.000	−0.003	−0.008
Market_Cap	0.040	0.184	0.425	−0.001	0.000	1.000	0.373	−0.010
PBV	0.044	−0.177	0.028	−0.004	−0.003	0.373	1.000	−0.015
Temp	−0.001	0.012	−0.003	−0.039	−0.008	−0.010	−0.015	1.000

where, Δ denotes the first variation factor, and k denotes the optimum length of the lag.

Two hypotheses are formulated to explore the long-term cointegration relationship between the variables:

$$\text{H0}: \theta 1 = \theta 2 = \theta 3 = \theta 4 = \theta 5 = \theta 6 = \theta 7 = 0 \text{ (no cointegration)}$$

$$\text{H1}: \theta 1 \neq \theta 2 \neq \theta 3 \neq \theta 4 \neq \theta 5 \neq \theta 6 \neq \theta 7 \neq 0 \text{ (cointegration exists)}$$

The *F*-test can examine both the null hypothesis of 'no cointegration' and the alternative hypothesis of 'cointegration exists.' A long-term relationship among the variables is indicated when the *F*-statistic surpasses the upper critical bound.

3.4 | NARDL Model

The model of asymmetric cointegration is as follows:

$$\begin{aligned} \text{RET}_{it} = {} & \alpha_0 + \alpha_1 \text{Beta}_{it} + \alpha_2 \text{EPS}_{it} + \alpha_3 \text{Market Cap}_{it} \\ & + \alpha_4 \text{PBV}_{it} + \alpha_5 \text{GSVI\_Climate}_{it} + \alpha_6 \text{Temp}^{+}{}_{it} \\ & + \alpha_7 \text{Temp}^{-}{}_{it} + \alpha_8 \text{GSVI\_Sentiment}^{+}{}_{it} \\ & + \alpha_9 \text{GSVI\_Sentiment}^{-}{}_{it} + \varepsilon_{it} \end{aligned} \tag{4}$$

where most of the definitions remain consistent with the previous context. People' attention to climate change and economic condition, represented as Temp_{it} and $\text{GSVI\_Sentiment}_{it}$, are transformed into positive and negative partial sums through decomposition:

$$\text{Temp}_t = \text{Temp}_0 + \text{Temp}^{+}{}_{t} + \text{Temp}^{-}{}_{t} \tag{5}$$

$$\text{Temp}^{+}{}_{t} = \sum_{i=1}^{t} \Delta\text{Temp}^{+}{}_{i} = \sum_{i=1}^{t} \max\left(\Delta\text{Temp}_i, 0\right) \tag{6}$$

TABLE 3 | Cross-sectional dependence tests.

Statistic	*t*-Stat	*p*
CIPS	−111.603	< 0.01
Truncated CIPS	−6.19	< 0.01

$$\text{Temp}^{-}{}_{t} = \sum_{i=1}^{t} \Delta\text{Temp}^{-}{}_{i} = \sum_{i=1}^{t} \min\left(\Delta\text{Temp}_i, 0\right) \tag{7}$$

$$\begin{aligned}\text{GSVI\_Sentiment}_t = {} & \text{GSVI\_Sentiment}_0 + \text{GSVI\_Sentiment}^{+}{}_{t} \\ & + \text{GSVI\_Sentiment}^{-}{}_{t}\end{aligned} \tag{8}$$

$$\begin{aligned}\text{GSVI\_Sentiment}^{+}{}_{t} &= \sum_{i=1}^{t} \Delta\text{GSVI\_Sentiment}^{+}{}_{i} \\ &= \sum_{i=1}^{t} \max\left(\Delta\text{GSVI\_Sentiment}_i, 0\right)\end{aligned} \tag{9}$$

TABLE 4 | Panel unit root tests.

	Intercept		Intercept and trend	
Variables	At level	At 1st difference	At level	At 1st difference
SET	−35.685***	−57.142***	−35.688***	−57.142***
Beta	−20.421***	−40.851***	−20.475***	−40.851***
EPS	−16.986***	−40.260***	−17.008***	−40.259***
GSVI_Climate	−24.579***	−43.822***	−24.580***	−43.822***
GSVI_Sentiment	−51.219***	−33.312***	−51.219***	−33.312***
Market Cap	−14.814***	−36.487***	−14.963***	−36.487***
PBV	−35.081***	−56.897***	−35.096***	−56.897***
Temp	−44.970***	−31.236***	−44.973***	−31.236***

Note: The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Regarding ADF individual unit root test, H_0: All panels contain unit roots (or all the series are non-stationary) and H_1: Some panels are stationary.

TABLE 5 | Linear ARDL estimation.

	Panel-ARDL analysis results					
	SET		Non-Green		Green	
Variable	Coef.	*t*-Stat	Coef.	*t*-Stat	Coef.	*t*-Stat
Beta	−0.144***	−37.145	−0.139***	−31.971	−0.142***	−12.915
Beta(−1)	0.142***	36.534	0.136***	31.171	0.140***	12.744
EPS	0.023***	38.156	0.023***	35.005	0.042***	27.257
EPS(−1)	−0.023***	−38.521	−0.024	−35.306	−0.042***	−27.332
GSVI_Climate	−0.001	−0.718	−0.003	−1.344	−0.003	−0.946
GSVI_Climate(−1)			−0.005**	−2.441	−0.004	−1.606
GSVI_Sentiment	−0.012*	−1.796	0.011	1.320	0.003	0.279
GSVI_Sentiment(−1)	0.016**	2.365			0.020*	1.797
Market_Cap	0.588***	197.582	0.586***	144.582	0.500***	94.081
Market_Cap(−1)	−0.587***	−197.442	−0.586***	−144.570	−0.500***	−94.133
PBV	0.000**	2.488	0.000**	2.123	0.075***	23.016
PBV(−1)	−0.000**	−2.517	−0.000**	−2.152	−0.076***	−23.049
Temp	0.000	0.278	0.000	−0.259	−0.002	−1.373
Temp(−1)						

Note: The symbols *, **, and *** denote the significance at the 10%, 5%, and 1% levels, respectively.

$$\text{GSVI\_Sentiment}^-{}_t = \sum_{i=1}^{t} \Delta\text{GSVI\_Sentiment}^-{}_i = \sum_{i=1}^{t} \min\left(\Delta\text{GSVI\_Sentiment}_i, 0\right) \tag{10}$$

where, Δ is the difference operator, indicating the partial amounts of positive and negative variations. The proposed NARDL model describes the asymmetric error-correction estimation (Shin, Yu, and Greenwood-Nimmo 2014) as follows:

$$\begin{aligned}\Delta\text{RET}_t = {} & \alpha_0 + \sum_{i=1}^{k} \alpha_{1j}\Delta\text{RET}_{t-i} + \sum_{i=0}^{k} \alpha_{2i}\Delta\text{Beta}_{t-i} \\ & + \sum_{i=0}^{k} \alpha_{3i}\Delta\text{EPS}_{t-i} + \sum_{i=0}^{k} \alpha_{4i}\ \Delta\text{Market Cap}_{t-i} \\ & + \sum_{i=0}^{k} \alpha_{5i}\ \Delta\text{PBV}_{t-i} + \sum_{i=0}^{k} \alpha_{6i}\ \Delta\text{GSVI\_Climate}_{t-i} \\ & + \sum_{i=0}^{k} \alpha_{7i}\ \Delta\text{Temp}^+{}_{t-i} + \sum_{i=0}^{k} \alpha_{8i}\ \Delta\text{Temp}^-{}_{t-i} \\ & + \sum_{i=0}^{k} \alpha_{9i}\ \Delta\text{GSVI\_Sentiment}^+{}_{t-i} \\ & + \sum_{i=0}^{k} \alpha_{10i}\ \Delta\text{GSVI\_Sentiment}^-{}_{t-i} + \rho_1\text{RET}_{t-1} \\ & + \rho_2\text{Beta}_{t-1} + \rho_3\text{EPS}_{t-1} + \rho_4\text{Market Cap}_{t-1} \\ & + \rho_5\text{PBV}_{t-1} + \rho_6\text{GSVI\_Climate}_{t-1} + \rho_7\text{Temp}^+{}_{t-1} \\ & + \rho_8\text{Temp}^-{}_{t-1} + \rho_9\text{GSVI\_Sentiment}^+{}_{t-1} \\ & + \rho_{10}\text{GSVI\_Sentiment}^-{}_{t-1} + \varepsilon_t\end{aligned} \tag{11}$$

where, k is the optimal length of the lag. Due to the improved explanatory properties and power, the Akaike Information Criterion (AIC) determines the optimal lag order.

4 | Empirical Results and Discussion

Below are the findings of the tests outlined in Section 3.

4.1 | Cross-Sectional Dependence Tests

In the initial phase of empirical research, addressing cross-sectional dependency is essential before conducting unit root tests on panel data, as highlighted by Rauf et al. (2018). Table 3 displays the outcomes of cross-sectional dependence tests, revealing the rejection of cross-sectional independence and confirming the presence of cross-sectional dependency.

4.1.1 | Unit Root Tests

To conduct cointegration tests, it is imperative to ascertain the integration order of each variable. Table 4 presents the outcomes of unit root tests applied to both the level and first difference forms. Employing stringent assumptions of the Fisher-ADF, it can be observed that all variables in their level are stationary at the 1% significance level.

4.2 | Discussing Linear ARDL Estimation

Table 5 summarises the linear ARDL model outcomes for the entire dataset, green stocks, and non-green stocks. The findings suggest that market capitalisation, beta, and EPS have the most significant impact on stock returns: an increase in market capitalisation of 1% increases 58.8% of stock market return; a negative coefficient of −0.144 of beta specifies a negative relationship between traditional systematic risk and stock market return of −14.4%; and an increase in 1% of EPS increases 2.3% of the stock market return. Climate risk factors (GSVI_climate and temperature anomalies) are generally not significant, except for GSVI_Climate's negative effect on non-green stocks. GSVI_Sentiment shows a small negative impact on aggregate market returns: an increase in awareness of the economic condition of 1% decreases the stock market return by 1.2%.

An analysis of Non-Green stocks shows similar results to those at the aggregate market level. Market capitalisation, beta, and EPS have the largest impact on Non-Green stock returns. Surprisingly, GSVI_Climate significantly affects Non-Green stock returns but is insignificant for Green stocks. The previous lag of GSVI_Climate has a negative coefficient of −0.005, indicating that a 1% increase in climate change awareness decreases Non-Green stock returns by 0.5%. Notably, our findings suggest that investor sentiment on climate issues is strongly linked to lower returns for emission-intensive stocks, mainly due to divestment. This aligns with the results of Santi (2023) and Baker and Wurgler (2007), who showed that stocks with high valuation uncertainty are most affected by sentiment. Since firms' environmental performance often involves subjective assessments, emission-intensive stocks are particularly vulnerable to sentiment-driven demand. Evaluating the relationship between environmental performance and firm value is complex due to several factors: the scarcity of accessible information on firms' environmental performance, the difficulty in processing this information, and the uncertain impact of government environmental policies and regulations on firm value.

Moreover, market sentiment regarding economic conditions has a more pronounced impact at the aggregate market level than the two subgroups. The market rate of return shows a significant negative correlation with current investor sentiment and a significant positive correlation with sentiment from the previous month. The coefficients suggest that a 1% increase in sentiment leads to a 1.2% decline in current month returns, followed by a 1.6% rise in the next month. This indicates that most of the sentiment's impact on returns dissipates within 1 month. These findings are consistent with those of Anusakumar, Ali, and Wooi (2017) and Kaplanski et al. (2015), who suggest a rally effect and highlight market inefficiency. The compounding impact shows that rising returns are linked to prior upward trends, implying that the causal relationship between sentiment and returns is not always one-directional. Examining the sentiment indicators used in our analysis reveals that many are directly or indirectly influenced by recent stock price movements, as reflected in stock returns. This suggests that market returns and investor sentiment are likely to influence each other simultaneously or with some delay (Santi 2023).

TABLE 6 | Linear ARDL estimation: Sub-periods, SET.

	Panel-ARDL analysis results					
	SET					
	2010–2014		2015–2019		2020–2023	
Variable	Coef.	*t*-Stat	Coef.	*t*-Stat	Coef.	*t*-Stat
Beta	−0.121***	−18.929	−0.859***	−67.129	−0.762***	−47.755
Beta(−1)	0.118***	18.531	0.855***	66.799	0.762***	47.795
EPS	0.031***	29.411	0.094***	51.331	0.090***	47.953
EPS(−1)	−0.031***	−29.904	−0.093***	−51.218	−0.091***	−48.196
GSVI_Climate	0.000	0.012	0.001	0.375	−0.008*	−1.841
GSVI_Climate(−1)						
GSVI_Sentiment	−0.020	−1.238	−0.028*	−1.872	−0.026	−1.294
GSVI_Sentiment(−1)					0.059***	2.926
Market_Cap	0.499***	98.136	0.435***	88.083	0.487***	85.632
Market_Cap(−1)	−0.498***	−97.881	−0.435***	−88.070	−0.487***	−85.602
PBV	0.000**	2.217	0.000***	7.064	0.000	0.570
PBV(−1)	−0.000*	−1.761	−0.000***	−6.708		
Temp	−0.001	−0.380	−0.002	−0.745	0.002	0.548
Temp(−1)						

Note: The symbols *, **, and *** denote the significance at the 10%, 5%, and 1% levels, respectively.

Considering fundamental factors, EPS and PBV are the most significant in influencing stock returns, particularly for Green stocks, with positive coefficients of 4.2% and 7.5%. In contrast, they exhibit much smaller coefficients of 2.3% and 0.0% for the aggregate market and Non-Green stocks. This suggests that investors place greater emphasis on fundamental factors when evaluating Green stocks, reflecting their confidence in environmentally responsible firms' financial performance and long-term value. However, temperature anomalies are insignificant across all three groups.

Additionally, we examined whether investor climate sentiment shows consistent short-term responses. We divided the data into three subperiods: 2010–2014, 2015–2019, and 2020–2023 (Tables 6–8). Our results in Table 6 indicate that market capitalisation, beta, and EPS consistently significantly impact stock returns. Beta, EPS, and GSVI_Sentiment notably show larger coefficients, reflecting a more pronounced short-term impact.

Importantly, GSVI_Sentiment exhibits the highest positive coefficient of 5.9% during 2020–2023, indicating heightened sensitivity to economic sentiment during the COVID-19 pandemic. The unprecedented economic disruptions likely intensified public focus on economic conditions, influencing investor behaviour more strongly than in previous periods. This suggests that public awareness of economic conditions becomes a critical driver of market reactions during crises, emphasising the need for investors to closely monitor sentiment indicators in volatile times.

GSVI_Climate becomes significant when the data is divided into sub-periods. The negative coefficient suggests that a 1% increase in climate change awareness reduces stock market returns in the short run, particularly in recent years.

Furthermore, idiosyncratic risk significantly affects stock returns, especially in the short term. Beta and EPS also have more pronounced effects on stock returns, with substantially larger coefficients across all three groups in the short term (Tables 6–8). PBV shows notably larger coefficients for Green stocks than for the aggregate market or Non-Green stocks. These findings confirm the strong influence of fundamental factors on Green stocks in both the long and short term, aligning with Bolton and Kacperczyk (2021), who argue that climate risk is strongly associated with firms having high book-to-market ratios and experiencing rapid revenue and earnings growth.

4.2.1 | Investor Attention to Climate Change

Regarding climate change risk factors, short-term analysis (Tables 6–8) reveals that GSVI_Climate and temperature anomalies significantly impact stock returns, especially for Green stocks, unlike long-term results. This indicates that Thai investor responses do not align with the expectation that long-term risks related to consumer, physical, and technological demand will become more pronounced (Bansal, Kiku, and Ochoa 2019; Krueger, Sautner, and Starks 2020; Amel-Zadeh 2021). Our findings partly confirm Hypothesis 1 by treating temperature anomalies as a novel form of systematic risk—similar to beta in the traditional CAPM but with distinct environmental and

TABLE 7 | Linear ARDL estimation: Sub-periods, NonGreen.

	Panel-ARDL analysis results					
	NonGreen					
	2010–2014		2015–2019		2020–2023	
Variable	**Coef.**	***t*-Stat**	**Coef.**	***t*-Stat**	**Coef.**	***t*-Stat**
Beta	−0.111***	−16.210	−0.808***	−56.115	−0.704***	−38.252
Beta(−1)	0.105***	15.366	0.803***	55.795	0.704***	38.217
EPS	0.027***	24.247	0.114***	49.749	0.096***	42.336
EPS(−1)	−0.027***	−24.558	−0.114***	−49.484	−0.097***	−42.535
GSVI_Climate	−0.018***	−3.657	−0.001	−0.319	0.004	0.800
GSVI_Climate(−1)	−0.007	−1.427	−0.008*	−1.652		
GSVI_Sentiment	−0.033*	−1.682	0.008	0.482	0.031	1.256
GSVI_Sentiment(−1)	0.030	1.521				
Market_Cap	0.494***	74.687	0.434***	67.784	0.504***	66.256
Market_Cap(−1)	−0.493***	−74.427	−0.435***	−67.889	−0.504***	−66.352
PBV	0.000	1.474	0.000***	6.823	−0.001***	−3.633
PBV(−1)			−0.000***	−6.466	0.001***	3.141
Temp	−0.001	−0.510	0.003	1.203	0.002	0.493
Temp(−1)						

Note: The symbols *, **, and *** denote the significance at the 10%, 5%, and 1% levels, respectively.

sustainability implications. Remarkably, temperature anomalies have smaller coefficients than beta.

When examining the short-term significance of climate change risk factors like GSVI_Climate and temperature anomalies for Green stocks (Table 8), it might be explained from following aspects: (1) Investors may quickly respond to climate-related risks in Green stocks closely tied to environmental outcomes. The modest coefficients indicate that while investors react to climate news, they view these short-term risks as minor, resulting in only small stock price adjustments. (2) Investors might overemphasise recent climate events, causing short-term market overreactions. This recency bias leads to rapid buying or selling of Green stocks based on the latest climate sentiment. However, since these reactions are sentiment-driven rather than based on long-term fundamentals, their impact on stock returns is typically small and short-lived. (3) Some investors speculate on market movements driven by climate news, creating volatility in Green stock prices. The small coefficients suggest that while speculative activity influences prices, it does so only modestly, as the fundamentals of Green stocks remain stable in the long term. (4) Investors may cautiously respond to climate risks by making minor portfolio adjustments or hedging strategies. The small coefficients indicate that these adjustments are not drastic, reflecting caution rather than alarm. (5) The short-term significance of climate factors may stem from temporary shifts in investor sentiment, leading to modest and fleeting changes in stock returns.

The results in Table 8 also show a robust, statistically significant positive correlation between individuals' climate change awareness and the returns of high ESG stocks (Green stocks). This aligns with prior research on investor sentiment and financial markets, indicating that heightened climate awareness leads to a preference for eco-friendly stocks, as demonstrated by Choi, Gao, and Jiang (2020). Investors actively manage climate risk exposure by favouring low-sensitivity stocks and divesting from high-sensitivity ones to achieve superior returns. Our research supports portfolio management guided by current climate information, involving long positions in climate-benefiting investments and short positions in climate-averse ones, as Engle et al. (2020) discussed.

Increased public attention to climate change can boost returns for sustainability-focused stocks by mobilising different investor groups (El Ouadghiri et al. 2021), including: (1) Reward highly sustainable companies by buying their shares and penalise less sustainable firms by divesting. (2) Conventional investors, influenced by growing climate concerns, transition into 'neo-sustainable' investors and favour stocks aligned with environmental and social factors (El Ouadghiri et al. 2021). (3) Self-interested investors recognise the heightened risks of conventional investments during periods of increased environmental awareness and act strategically. They anticipate a surge in demand for sustainable companies' shares from traditional sustainable investors and aim to secure a first-mover advantage.

TABLE 8 | Linear ARDL estimation: Sub-periods, Green.

	Panel-ARDL analysis results					
	Green					
	2010–2014		2015–2019		2020–2023	
Variable	Coef.	*t*-Stat	Coef.	*t*-Stat	Coef.	*t*-Stat
Beta	−0.094***	−4.899	−0.577***	−21.299	−0.495***	−16.442
Beta(−1)	0.092***	4.813	0.575***	21.238	0.490***	16.284
EPS	0.138***	37.652	0.077***	31.805	0.111***	33.218
EPS(−1)	−0.140***	−37.921	−0.077***	−31.720	−0.111***	−33.149
GSVI_Climate	0.000	0.064	0.015**	2.077	0.000	−0.040
GSVI_Climate(−1)	0.009*	1.767				
GSVI_Sentiment	−0.030	−1.188	0.028	1.019	−0.017	−0.549
GSVI_Sentiment(−1)					0.066**	2.060
Market_Cap	0.363***	40.161	0.358***	38.760	0.329***	30.523
Market_Cap(−1)	−0.363***	−40.209	−0.358***	−38.761	−0.329***	−30.523
PBV	0.103***	16.279	0.077***	13.001	0.095***	13.372
PBV(−1)	−0.103***	−16.233	−0.077***	−12.931	−0.096***	−13.620
Temp	−0.006*	−1.696	0.001	0.419	0.000	−0.048
Temp(−1)						

Note: The symbols *, **, and *** denote the significance at the 10%, 5%, and 1% levels, respectively.

Conversely, increased public attention to climate change decreases Non-Green stock returns (Table 7). This confirms our hypothesis that high-sustainability companies outperform low-sustainability ones when climate change awareness rises, highlighting a growing investor preference for environmentally responsible firms. For Non-Green companies, this suggests a rising risk premium as investors anticipate potential regulatory changes, reputational damage, and shifting consumer preferences away from environmentally harmful practices. These firms may face increasing pressure to adopt more sustainable practices or risk market penalties.

4.2.2 | Industrial Sector Analysis

Academic research has shown that stock returns respond differently to climate change risk across industry sectors (Addoum, Ng, and Ortiz-Bobea 2021; Amel-Zadeh 2021). To account for this, we refined the distinct effects within different sectors, as classified by the Stock Exchange of Thailand (SET 2021). We examined eight sectors: Agro & Food Industry (AGRO), Consumer Products (CONSUMP), Financials (FINCIAL), Industrials (INDUS), Property & Construction (PROPCON), Resources (RESOURCES), Services (SERVICES), and Technology (TECH).

Table 9 presents our findings. When analysing the impact of new systematic risks (temperature anomalies) within these sectors, we find that industry-level stock returns are generally not sensitive to extreme temperatures. However, temperature anomalies affect only stock returns in the consumer products sector. In traditional systematic risk, beta plays a more significant role, as it is significantly linked to stock returns across all eight industries.

As expected, our empirical findings reveal differences in how industry-level stock returns respond to public attention to climate change compared to returns categorised by ESG responsibility. The financials and services sectors are the most responsive to public attention to climate change. This contrasts with previous research, which suggested that the financial sector may show lower environmental awareness and be less reactive to environmentally friendly sentiment indicators (Auer and Schumacher 2016).

Our results in Tables 5 and 9 highlight that public attention to climate change has a greater impact on stock returns when considering ESG responsibility. Therefore, using a nonlinear framework, we further explore the relationship between temperature anomalies, GSVI_Sentiment, and stock returns within ESG contexts.

4.3 | Discussing Nonlinear ARDL Estimation

We address a standard modelling limitation in previous research. The autoregressive distributed lag (ARDL) model is often used in climate finance studies to examine the relationship between financial and economic stability, development, and environmental risks, typically assuming linear

TABLE 9 | Linear ARDL estimation (industry level).

	Panel-ARDL analysis results							
	AGRO		CONSUMP		FINCIAL		INDUS	
Variable	**Coef.**	***t*-Stat**	**Coef.**	***t*-Stat**	**Coef.**	***t*-Stat**	**Coef.**	***t*-Stat**
Beta	0.037*	1.714	−0.475***	−17.971	−0.045***	−4.877	−0.496***	−26.599
Beta(−1)	−0.041*	−1.880	0.472***	17.896	0.045***	4.909	0.495***	26.553
EPS	0.082***	28.519	0.042***	25.961	0.031***	16.925	0.007***	8.876
EPS(−1)	−0.081***	−28.403	−0.043***	−26.274	−0.031***	−17.040	−0.007***	−9.044
GSVI_Climate	0.003	0.846	−0.006	−1.259	−0.016***	−3.425	0.003	0.875
GSVI_Climate(−1)							0.006	1.523
GSVI_Sentiment	−0.017	−0.973	0.001	0.049	0.029	1.411	−0.016	−0.973
GSVI_Sentiment(−1)			0.056**	2.400				
Market_Cap	0.559***	61.792	0.483***	40.846	0.413***	48.468	0.801***	89.116
Market_Cap(−1)	−0.560***	−61.832	−0.482***	−40.810	−0.413***	−48.508	−0.801***	−89.104
PBV	0.034***	9.867	0.008***	2.957	0.096***	14.636	0.000***	5.043
PBV(−1)	−0.034***	−10.008	−0.007***	−2.698	−0.096***	−14.567	−0.000***	−4.897
Temp	−0.000	−0.064	−0.003***	−0.971	−0.003	−1.141	0.000	−0.175
Temp(−1)								
	PROPCON		RESOURCE		SERVICES		TECH	
Variable	**Coef.**	***t*-Stat**	**Coef.**	***t*-Stat**	**Coef.**	***t*-Stat**	**Coef.**	***t*-Stat**
Beta	−0.419***	−21.068	−0.127***	−5.851	−0.726***	−33.725	−0.167***	−8.463
Beta(−1)	0.417***	20.982	0.127***	5.875	0.723***	33.558	0.165***	8.364
EPS	0.047***	12.844	0.019***	10.344	0.100***	34.282	0.033***	11.401
EPS(−1)	−0.047***	−12.833	−0.020***	−10.466	−0.101***	−34.611	−0.033***	−11.500
GSVI_Climate	−0.004	−1.140	0.003	0.627	0.008**	1.994	−0.002	−0.377
GSVI_Climate(−1)								
GSVI_Sentiment	0.019	1.111	0.006	0.327	−0.004	−0.204	−0.012	−0.581
GSVI_Sentiment(−1)								
Market_Cap	0.490***	64.399	0.697***	89.468	0.511***	66.281	0.753***	94.738
Market_Cap(−1)	−0.490***	−64.392	−0.697***	−89.435	−0.511***	−66.224	−0.753***	−94.800
PBV	0.076***	16.858	0.043***	9.505	0.000	0.292	0.001***	3.517
PBV(−1)	−0.077***	−17.035	−0.047***	−10.563			−0.001***	−3.638
Temp	−0.001	−0.415	−0.002	−0.598	0.003	0.911	0.001	0.328
Temp(−1)					−0.004	−1.439		

Note: The symbols *, **, and *** denote the significance at the 10%, 5%, and 1% levels, respectively.

relationships (e.g., Shahbaz, Tiwari, and Nasir 2013; Abbasi and Riaz 2016; Shoaib et al. 2020). However, Thampanya, Wu, and Cowton (2021) argue that the connection between financial variables and climate risk varies across nations with different income levels and is more pronounced when non-linearity is considered. Relying solely on linear methods may introduce estimation bias and produce misleading results by overlooking the varied impacts of climate change on financial variables. Therefore, we use the NARDL model, which allows us to identify asymmetric relationships between stock returns, a new type of systematic risk (temperature anomaly), and the sentiment factor (GSVI_Sentiment). Additional explanatory variables in our stock returns model include beta, EPS, market capitalisation, PBV, and GSVI_Climate.

Table 10 presents the NARDL model results. As described in Equations (5) and (8), temperature anomalies and GSVI_Sentiment are divided into positive and negative shocks.

TABLE 10 | Nonlinear ARDL estimation.

	Panel-ARDL analysis results					
	SET		Non-Green		Green	
Variable	**Coef.**	***t*-Stat**	**Coef.**	***t*-Stat**	**Coef.**	***t*-Stat**
Beta	−0.144***	−37.260	−0.139***	−31.971	−0.142***	−12.933
Beta(−1)	0.142***	36.652	0.136***	31.159	0.140***	12.772
EPS	0.023***	38.229	0.023***	35.004	0.042***	27.255
EPS(−1)	−0.023***	−38.594	−0.024***	−35.312	−0.042***	−27.322
GSVI_Climate	−0.001	−0.827	−0.003	−1.415	−0.003	−1.094
GSVI_Climate(−1)			−0.005**	−2.486	−0.004*	−1.655
GSVI_Sentiment_POS	0.007	0.727	0.012	1.425	0.026	1.614
GSVI_Sentiment_POS(−1)						
GSVI_Sentiment_NEG	−0.027***	−3.378	0.007	0.864	−0.016	−1.166
GSVI_Sentiment_NEG(−1)	0.030***	2.767			0.043**	2.401
Market_Cap	0.588***	198.331	0.586***	144.560	0.499***	94.039
Market_Cap(−1)	−0.588***	−198.203	−0.586***	−144.553	−0.500***	−94.109
PBV	0.000**	2.493	0.000**	2.117	0.075***	22.995
PBV(−1)	−0.000**	−2.526	−0.000**	−2.150	−0.075***	−23.030
Temp_POS	−0.003	−1.487	−0.001	−0.832	−0.002	−1.258
Temp_POS(−1)	0.003	1.467				
Temp_NEG	0.001	0.844	0.000	−0.026	−0.002	−1.574
Temp_NEG(−1)						

Note: The symbols *, **, and *** denote the significance at the 10%, 5%, and 1% levels, respectively.

Notably, our analysis reveals asymmetric effects. Interestingly, GSVI_Climate significantly impacts Green stock returns when applying a nonlinear framework. Small negative coefficients of −0.5% for Non-Green and −0.4% for Green stocks are observed, showing that investors do not respond to climate-related public attention (GSVI_Climate) in a straightforward, proportional way. Instead, their reactions are nonlinear, indicating that investor sentiment and decision-making are more complex than previously thought. This finding enhances our understanding of how climate information influences investors, especially concerning Green stocks. Our results align with those of Choi, Gao, and Jiang (2020) and Engle et al. (2020). As climate awareness rises, investors adjust their firm valuations, considering that companies exposed to adverse climate effects may face negative impacts from stricter environmental regulations, increasing production costs.

Tables 11–13 present the results from short-term analysis of aggregate market, Non-Green, and Green stocks, respectively. Additionally, temperature anomalies remain insignificant across the three sub-periods for aggregate market (Table 11). However, they significantly affect stock returns in the short term for Non-Green and Green stocks (Tables 12 and 13), with more pronounced effects on Non-Green stocks. Asymmetric relationships also emerge, where positive shocks have a stronger impact. Different signs for current and lagged temperature anomalies suggest the effects cancel out within a month. Nonetheless, the overall impact on Non-Green and Green stocks is relatively small, ranging from 1.3% to 3.2%.

Comparing results from linear and nonlinear frameworks, temperature anomalies linearly affect Green companies' stock returns. In contrast, under the nonlinear assumption, temperature anomalies have a more significant impact on Non-Green stocks. The linear effect on Green stocks implies that investors may have a more stable, predictable view of these companies' ability to manage climate risks. This suggests they perceive Green firms as more resilient to climate risks, leading to steadier stock performance.

Adverse shocks related to public attention to economic conditions have a stronger impact on stock market returns, indicating that reduced awareness of economic conditions leads to higher stock returns than increased awareness. One possible explanation is that markets may behave counterintuitively when economic awareness declines, potentially due to reduced risk aversion among investors or a shift in focus to market sentiment or speculative opportunities.

TABLE 11 | Nonlinear ARDL estimation: Sub-periods, SET.

	Panel-ARDL analysis results					
	SET					
	2010–2014		2015–2019		2020–2023	
Variable	**Coef.**	***t*-Stat**	**Coef.**	***t*-Stat**	**Coef.**	***t*-Stat**
Beta	−0.121***	−18.924	−0.859	−67.153	−0.764***	−48.007
Beta(−1)	0.118***	18.523	0.855	66.822	0.764***	48.041
EPS	0.031***	29.378	0.094	51.324	0.090***	47.998
EPS(−1)	−0.031***	−29.878	−0.093	−51.208	−0.091***	−48.242
GSVI_Climate	0.000	0.059	0.001	0.191	−0.008*	−1.768
GSVI_Climate(−1)						
GSVI_Sentiment_POS	−0.080***	−3.659	0.002	0.183	0.001	0.082
GSVI_Sentiment_POS(−1)	0.080***	3.917				
GSVI_Sentiment_NEG	0.050**	2.367	−0.051	−2.931	−0.073***	−3.144
GSVI_Sentiment_NEG(−1)	−0.050**	−2.195	0.053	2.644	0.074***	2.803
Market_Cap	0.498***	97.818	0.435	88.041	0.488***	85.885
Market_Cap(−1)	−0.497***	−97.573	−0.435	−88.017	−0.488***	−85.876
PBV	0.000**	2.179	0.000	6.976	0.000	0.585
PBV(−1)	−0.000*	−1.737	0.000	−6.624		
Temp_POS	0.000	−0.039	0.009	1.942	0.000	−0.051
Temp_POS(−1)			−0.009	−2.072		
Temp_NEG	0.000	−0.051	−0.011	−2.721	0.000	−0.032
Temp_NEG(−1)			0.011	2.637		

Note: The symbols *, **, and *** denote the significance at the 10%, 5%, and 1% levels, respectively.

5 | Conclusion

This study broadens our understanding of how climate-related risks, particularly temperature anomalies, function as a novel form of systematic risk in financial markets. Our findings suggest that temperature anomalies, equivalent to traditional market risks like beta in the CAPM framework, notably influence stock returns, particularly when analysed through an ESG lens. This research reveals that temperature anomalies do not uniformly impact all stocks but have a more pronounced short-term effect on sustainability-focused companies (Green stocks) than less eco-friendly firms (Non-Green stocks). This suggests that climate risks are becoming increasingly integrated into investor decision-making, reflecting an evolving financial landscape where environmental concerns are no longer peripheral but central to risk assessment and portfolio management.

The core theoretical contribution of this study lies in identifying temperature anomalies as a form of systematic risk, expanding the boundaries of the traditional risk–return relationship that financial metrics like beta have long dominated. By doing so, we demonstrate that climate risks are not only externalities but integral factors influencing financial markets. The nonlinear relationship between temperature anomalies and stock returns, particularly for Non-Green firms, highlights the complexity of investor behaviour in response to climate risks. It seems that investors may underreact to gradual climate risks while overreacting to more severe or immediate anomalies. This nuanced perspective aligns with behavioural finance theories, where cognitive biases and sentiment play a significant role in decision-making, especially in the context of ESG factors.

Moreover, including the GSVI as a proxy for public awareness adds a behavioural dimension to our findings. The nonlinear impact of public attention on economic conditions suggests that investors are not only passive recipients of climate information but also actively respond to shifts in sentiment. The more substantial impact of negative economic news on stock returns further supports the idea that investor sentiment, shaped by public awareness, can lead to significant market movements. This finding has profound implications for understanding market volatility during periods of heightened climate risk awareness, especially in emerging markets like Thailand, where the effects of climate change are more acute.

From a practical perspective, our research provides valuable insights for investors, portfolio managers, and policymakers.

TABLE 12 | Nonlinear ARDL estimation: Sub-periods, NonGreen.

	Panel-ARDL analysis results					
	NonGreen					
	2010–2014		2015–2019		2020–2023	
Variable	**Coef.**	***t*-Stat**	**Coef.**	***t*-Stat**	**Coef.**	***t*-Stat**
Beta	−0.111***	−16.266	−0.808***	−56.126	−0.705***	−38.308
Beta(−1)	0.105***	15.385	0.803***	55.804	0.705***	38.273
EPS	0.027***	24.213	0.114***	49.733	0.096***	42.337
EPS(−1)	−0.027***	−24.533	−0.114***	−49.463	−0.097***	−42.538
GSVI_Climate	−0.018***	−3.737	−0.001	−0.230	0.006	1.155
GSVI_Climate(−1)	−0.007	−1.431	−0.007	−1.461		
GSVI_Sentiment_POS	−0.045**	−2.063	0.064***	2.948	0.001	0.379
GSVI_Sentiment_POS(−1)	0.045**	2.033	−0.064***	−2.943		
GSVI_Sentiment_NEG	0.000	−0.240	−0.037*	−1.662	0.047	1.636
GSVI_Sentiment_NEG(−1)			0.037*	1.670	−0.047	−1.619
Market_Cap	0.493***	74.457	0.433***	67.671	0.504***	66.313
Market_Cap(−1)	−0.491***	−74.195	−0.434***	−67.783	−0.505***	−66.412
PBV	0.000	1.486	0.000***	6.832	−0.001***	−3.592
PBV(−1)			−0.000***	−6.452	0.001***	3.101
Temp_POS	−0.019***	−3.176	0.003	1.100	0.026***	3.195
Temp_POS(−1)	0.017***	2.884			−0.024***	−3.047
Temp_NEG	0.013**	2.493	0.003	1.097	−0.016**	−2.212
Temp_NEG(−1)	−0.015***	−2.837			0.017**	2.399

Note: The symbols *, **, and *** denote the significance at the 10%, 5%, and 1% levels, respectively.

For investors, particularly those focused on ESG investing, the findings highlight the importance of integrating climate risk assessments into their decision-making processes. Temperature anomalies and their short-term effects on Green stocks suggest that sustainable investments may offer a form of resilience against climate risks, albeit with some volatility. Investors may need to adopt a more dynamic approach, balancing short-term market reactions with long-term strategic goals. This is especially relevant given the rapid absorption of climate-related information into stock prices, as evidenced by the immediate but short-lived effects of temperature anomalies on Green stock returns.

Portfolio managers, in particular, should consider temperature anomalies alongside traditional financial metrics in their risk assessment models. The nonlinear effects observed in Non-Green stocks indicate that climate risks may not always manifest in predictable ways, requiring more sophisticated risk management tools that account for both linear and nonlinear dynamics. Furthermore, the role of investor sentiment, as captured by the GSVI, suggests that market sentiment analysis could be a valuable tool for anticipating short-term market shifts related to climate news.

For policymakers, this study enlightens the need for a more proactive approach to integrating climate risks into financial regulation and market oversight. As climate change becomes an increasingly salient factor in financial markets, regulatory frameworks must evolve to ensure that investors and companies are adequately prepared for the economic impacts of environmental risks. Encouraging greater transparency and disclosure of climate-related risks, particularly for companies with weaker ESG credentials, could help mitigate the market's tendency to underreact to gradual climate risks while overreacting to severe anomalies.

To conclude, this study highlights the growing relevance of climate risks in financial markets. It provides a framework for understanding how temperature anomalies function as a new form of systematic risk. By examining the interplay between temperature anomalies, investor sentiment, and stock returns, we offer a fresh perspective on how climate change reshapes investor behaviour and market dynamics. The implications of our findings are far-reaching, offering theoretical and practical insights for a wide range of stakeholders. As climate change continues to accelerate, investors, portfolio managers, and policymakers need to adapt their strategies and frameworks to account for this new form of risk will only become more urgent.

TABLE 13 | Nonlinear ARDL estimation: Sub-periods, Green.

	Panel-ARDL analysis results					
	Green					
	2010–2014		2015–2019		2020–2023	
Variable	**Coef.**	***t*-Stat**	**Coef.**	***t*-Stat**	**Coef.**	***t*-Stat**
Beta	−0.092***	−4.782	−0.576***	−21.269	−0.496***	−16.445
Beta(−1)	0.090***	4.705	0.574***	21.213	0.491***	16.285
EPS	0.138***	37.578	0.077***	31.817	0.111***	33.193
EPS(−1)	−0.140***	−37.857	−0.077***	−31.739	−0.111***	−33.114
GSVI_Climate	0.002	0.315	0.015	2.081	0.001	0.185
GSVI_Climate(−1)	0.010**	1.980				
GSVI_Sentiment_POS	0.003	0.141	0.006	0.332	−0.071*	−1.775
GSVI_Sentiment_POS(−1)					0.096**	2.153
GSVI_Sentiment_NEG	0.003	0.149	0.007	0.360	0.025	0.660
GSVI_Sentiment_NEG(−1)						
Market_Cap	0.363***	40.079	0.358***	38.721	0.329***	30.483
Market_Cap(−1)	−0.363***	−40.125	−0.358***	−38.712	−0.329***	−30.510
PBV	0.103***	16.171	0.077***	13.021	0.094***	13.346
PBV(−1)	−0.103***	−16.123	−0.077***	−12.951	−0.096***	−13.603
Temp_POS	−0.032***	−3.815	−0.001	−0.366	0.000	0.048
Temp_POS(−1)	0.032***	3.911				
Temp_NEG	0.014**	1.978	−0.001	−0.399	0.000	0.033
Temp_NEG(−1)	−0.014**	−1.974				

Note: The symbols *, **, and *** denote the significance at the 10%, 5%, and 1% levels, respectively.

While our study offers valuable contributions, we must acknowledge certain limitations. First, our focus on a single country with a relatively small sample of firms and a 14-year time frame may limit the generalisability of the results. Additionally, using the GSVI as a proxy for climate awareness, rather than direct surveys, may introduce measurement constraints. Future research should address these limitations by expanding to multiple countries, extending the time horizon, using alternative measures of climate awareness, and testing our findings across different market conditions to strengthen the robustness and applicability of our conclusions.

Acknowledgements

We greatly appreciate the constructive comments provided by the associate editor and two anonymous reviewers, which helped significantly improve the quality of our paper.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

[1] As an illustration, The World Bank Group (2021a) documented a consistent rise in temperatures and annual precipitation in Thailand since the mid-20th century. Projections indicate that the average temperature may increase by 0.95°C–3.23°C above the 1986–2005 baseline by the close of the 21st century, contingent on future CO_2 emissions. Among Thailand's natural hazards, temperature anomalies have emerged as the most severe, exerting significant economic and human impacts.

[2] In 2022, The Global Economy ranked SET as the 8th largest by traded value, 12th by the number of listed companies, and 18th by market capitalisation worldwide.

References

Abbasi, F., and K. Riaz. 2016. "CO_2 Emissions and Financial Development in an Emerging Economy: An Augmented VAR Approach." *Energy Policy* 90: 102–114.

Addoum, J. M., D. T. Ng, and A. Ortiz-Bobea. 2020. "Temperature Shocks and Establishment Sales." *Review of Financial Studies* 33, no. 3: 1331–1366.

Addoum, J. M., D. T. Ng, and A. Ortiz-Bobea. 2021. "Temperature Shocks and Industry Earnings News." Available at SSRN 3480695.

Albertini, E. 2019. “The Contribution of Management Control Systems to Environmental Capabilities.” *Journal of Business Ethics* 159, no. 4: 1163–1180.

Amel-Zadeh, A. 2021. “The Financial Materiality of Climate Change: Evidence From a Global Survey.” Available at SSRN 3295184.

Anastasiou, D., and K. Drakos. 2021. “Nowcasting the Greek (Semi-) Deposit Run: Hidden Uncertainty About the Future Currency in a Google Search.” *International Journal of Finance and Economics* 26: 1133–1150.

Anusakumar, S. V., R. Ali, and H. C. Wooi. 2017. “The Effect of Investor Sentiment on Stock Returns: Insight From Emerging Asian Markets.” *Asian Academy of Management Journal of Accounting and Finance* 13: 159–178.

Ardia, D., K. Bluteau, K. Boudt, and K. Inghelbrecht. 2022. “Climate Change Concerns and the Performance of Green vs. Brown Stocks.” *Management Science* 69, no. 12: 7607–7632.

Aristei, D., and D. Martelli. 2014. “Sovereign Bond Yield Spreads and Market Sentiment and Expectations: Empirical Evidence From Euro Area Economies.” *Journal of Economics and Business* 76: 55–84.

Attig, N., S. El Ghoul, O. Guedhami, and J. Suh. 2013. “Corporate Social Responsibility and Credit Ratings.” *Journal of Business Ethics* 117, no. 4: 679–694.

Auer, B. R., and F. Schumacher. 2016. “Do Socially (Ir)responsible Investment Pay? New Evidence From International ESG Data.” *Quarterly Review of Economics and Finance* 59: 51–62.

Baker, M., and J. Wurgler. 2006. “Investor Sentiment and the Cross-Section of Stock Returns.” *Journal of Finance* 61, no. 4: 1645–1680.

Baker, M., and J. Wurgler. 2007. “Investor Sentiment in the Stock Market.” *Journal of Economic Perspectives* 21, no. 2: 129–152.

Balvers, R., D. Du, and X. Zhao. 2017. “Temperature Shocks and the Cost of Equity Capital: Implications for Climate Change Perceptions.” *Journal of Banking & Finance* 77: 18–34.

Bansal, R., D. Kiku, and M. Ochoa. 2019. *Climate Change Risk*. Cambridge, MA: National Bureau of Economic Research.

Barber, B. M., and T. Odean. 2008. “All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors.” *Review of Financial Studies* 21, no. 2: 785–818.

Bolton, P., and M. Kacperczyk. 2021. “Do Investors Care About Carbon Risk?” *Journal of Financial Economics* 142: 517–549.

Choi, D., Z. Gao, and W. Jiang. 2020. “Attention to Global Warming.” *Review of Financial Studies* 33, no. 3: 1112–1145.

Da, Z., J. Engelberg, and P. Gao. 2011. “In Search of Attention.” *Journal of Finance* 66, no. 5: 1461–1499.

De Long, B. J., A. Shleifer, L. H. Summers, and R. J. Waldmann. 1990. “Noise Trader Risk in Financial Markets.” *Journal of Political Economy* 98: 703–738.

Dell, M., B. F. Jones, and B. A. Olken. 2012. “Temperature Shocks and Economic Growth: Evidence From the Last Half Century.” *American Economic Journal: Macroeconomics* 4, no. 3: 66–95.

Dutordoir, M., N. C. Strong, and P. Sun. 2018. “Corporate Social Responsibility and Seasoned Equity Offerings.” *Journal of Corporate Finance* 50: 158–179.

El Ouadghiri, I., K. Guesmi, J. Peillex, and A. Ziegler. 2021. “Public Attention to Environmental Issues and Stock Market Returns.” *Ecological Economics* 180: 106836.

Elijido-Ten, E. O., and P. Clarkson. 2019. “Going Beyond Climate Change Risk Management: Insights From the World's Largest Most Sustainable Corporations.” *Journal of Business Ethics* 157, no. 4: 1067–1089.

Engle, R. F., S. Giglio, B. Kelly, H. Lee, and J. Stroebel. 2020. “Hedging Climate Change News.” *Review of Financial Studies* 33, no. 3: 1184–1216.

Faccini, R., R. Matin, and G. Skiadopoulos. 2023. “Dissecting Climate Risks: Are They Reflected in Stock Prices?” *Journal of Banking and Finance* 155: 106948.

Fama, E. F., and K. R. French. 1993. “Common Risk Factors in the Returns on Stocks and Bonds.” *Journal of Financial Economics* 33, no. 1: 3–56.

Giese, G., L. E. Lee, D. Melas, Z. Nagy, and L. Nishikawa. 2019. “Foundations of ESG Investing: How ESG Affects Equity Valuation, Risk and Performance.” *Journal of Portfolio Management* 45, no. 5: 69–83.

Hart, S. L., and G. Dowell. 2011. “Invited Editorial: A Natural-Resource-Based View of the Firm: Fifteen Years After.” *Journal of Management* 37, no. 5: 1464–1479.

Herrnstadt, E., and E. Muehlegger. 2014. “Weather, Salience of Climate Change and Congressional Voting.” *Journal of Environmental Economics and Management* 68, no. 3: 435–448.

Hirshleifer, D., and S. H. Teoh. 2003. “Limited Attention, Information Disclosure, and Financial Reporting.” *Journal of Accounting and Economics* 36, no. 1–3: 337–386.

Hjort, I. 2016. *Potential Climate Risks in Financial Markets: Report From a Workshop*. Memorandum no. 02/2016. Oslo, Norway: Department of Economics, University of Oslo.

Kaplanski, G., H. Levy, C. Veld, and Y. Veld-Merkoulova. 2015. “Do Happy People Make Optimistic Investors?” *Journal of Financial and Quantitative Analysis* 50: 145–168.

Khan, M., G. Serafeim, and A. Yoon. 2016. “Corporate Sustainability: First Evidence on Materiality.” *Accounting Review* 91: 1697–1724.

Kim, Y., H. Li, and S. Li. 2014. “Corporate Social Responsibility and Stock Price Crash Risk.” *Journal of Banking & Finance* 43: 1–13.

Krueger, P., Z. Sautner, and L. T. Starks. 2020. “The Importance of Climate Risks for Institutional Investors.” *Review of Financial Studies* 33, no. 3: 1067–1111.

Kumar, A., W. Xin, and C. Zhang. 2019. *Climate Sensitivity and Predictable Returns*. https://doi.org/10.2139/ssrn.3331872.

Kumari, J., and J. Mahakud. 2015. “Does Investor Sentiment Predict the Asset Volatility? Evidence From Emerging Stock Market India.” *Journal of Experimental Finance* 8: 25–39.

Lopatta, K., F. Buchholz, and T. Kaspereit. 2016. “Asymmetric Information and Corporate Social Responsibility.” *Business & Society* 55, no. 3: 458–488.

Lucas, E. C., and W. Mendes-Da-Silva. 2018. “Impact of Climate on Firm Value: Evidence From the Electric Power Industry in Brazil.” *Energy* 153: 359–368.

Mason, C. F. 2013. “The Economics of Eco-Labeling: Theory and Empirical Implications.” *International Review of Environmental and Resource Economics* 6, no. 4: 341–372.

Merton, R. 1987. “A Simple Model of Capital Market Equilibrium With Incomplete Information.” *Journal of Finance* 42, no. 3: 483–510.

Nagar, V., and J. Schoenfeld. 2021. “Is Weather a Systematic Risk? Evidence From Annual Reports.” Available at SSRN, 3438428.

Nandy, M., and S. Lodh. 2012. “Do Banks Value the Eco-Friendliness of Firms in Their Corporate Lending Decision? Some Empirical Evidence.” *International Review of Financial Analysis* 25: 83–93.

NGFS. 2020. *Overview of Environmental Risk Analysis by Financial Institution: Technical Report*. Paris, France: Network for Greening the Financial System.

Pesaran, M. H., Y. Shin, and R. Smith. 2001. “Bound Testing Approaches to the Analysis of Level Relationships.” *Journal of Applied Economics* 16: 289–326.

Pástor, L., R. F. Stambaugh, and L. A. Taylor. 2021. "Sustainable Investing in Equilibrium." *Journal of Financial Economics* 142, no. 2: 550–571.

Rao, S., S. Koirala, C. Thapa, and S. Neupane. 2021. "When Rain Matters! Investments and Value Relevance." *Journal of Corporate Finance* 73: 101827.

Rauf, A., X. Liu, W. Amin, I. Ozturk, O. U. Rehman, and M. Hafeez. 2018. "Testing EKC Hypothesis With Energy and Sustainable Development Challenges: A Fresh Evidence From Belt and Road Initiative Economies." *Environmental Science and Pollution Research* 25: 32066–32080.

Santi, C. 2023. "Investor Climate Sentiment and Financial Markets." *International Review of Financial Analysis* 86: 102490.

Shahbaz, M., A. K. Tiwari, and M. Nasir. 2013. "The Effects of Financial Development, Economic Growth, Coal Consumption and Trade Openness on CO_2 Emissions in South Africa." *Energy Policy* 61: 1452–1459.

Shin, Y., B. Yu, and M. Greenwood-Nimmo. 2014. "Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework." In *Festschrift in Honor of Peter Schmidt*, edited by R. Sickles and W. Horrace, 281–314. New York: Springer.

Shoaib, H. M., M. Z. Rafique, A. M. Nadeem, and S. Huang. 2020. "Impact of Financial Development on CO_2 Emissions: A Comparative Analysis of Developing Economies (D8) and Developed Economies (G8)." *Environmental Science and Pollution Research* 27, no. 11: 12461–12475.

Thampanya, N., J. Wu, and C. Cowton. 2021. "Carbon Neutrality Targets, Optimal Environmental Management Strategies & the Role of Financial Development: New Evidence Incorporating Nonlinear Effects and Different Income Levels." *Journal of Environmental Management* 297: 113352.

The Stock Exchange of Thailand. 2021. "SET Industry Group and Sector Classification."

The World Bank Group. 2021a. "Climate Risk Country Profile—Thailand."

The World Bank Group. 2021b. "Climate Change Knowledge Portal."

Trapp, N. L. 2014. "Stakeholder Involvement in CSR Strategy-Making? Clues From Sixteen Danish Companies." *Public Relations Review* 40, no. 1: 42–49.

Tzomakas, C., D. Anastasiou, A. Katsafados, and S. I. Krokida. 2023. "Crisis Sentiment and Banks' Stock Price Crash Risk: A Missing Piece?" *Journal of International Financial Markets, Institutions & Money* 87: 101806.

Tzouvanas, P., R. Kizys, I. Chatziantoniou, and R. Sagitova. 2019. "Can Variations in Temperature Explain the Systemic Risk of European Firms?" *Environmental and Resource Economics* 74, no. 4: 1723–1759.

Venturini, A. 2022. "Climate Change, Risk Factors and Stock Returns: A Review of the Literature." *International Review of Financial Analysis* 79: 101934.

Yang, R., C. W. Wong, and X. Miao. 2020. "Analysis of the Trend in the Knowledge of Environmental Responsibility Research." *Journal of Cleaner Production* 278, no. 1: 123402.