ISSN 1611-1699 / eISSN 2029-4433

JOURNAL of BUSINESS ECONOMICS & MANAGEMENT

2026
Volume 27
Issue 4
Pages 781–800
https://doi.org/10.3846/jbem.2026.28069

THE IMPACT OF CLIMATE RISK ATTENTION ON EXCESS RETURNS OF ACTIVELY MANAGED FUNDS

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Article History:
- received 9 October 2025
- accepted 17 June 2026

Abstract. This study constructs a climate risk attention indicator for Chinese funds by applying Word2Vec-based text analysis to annual fund reports. This study examines how climate risk attention affects excess returns in actively managed funds, using the Brinson model for performance decomposition. The results show that climate risk attention increases fund excess returns with notable heterogeneity: a 1% increase in acute physical risk attention raises excess returns by 24.675%, whereas the same increase in transition risk attention leads to a much smaller effect—only 2.746%, approximately 11% of the acute risk impact. Chronic physical risks, such as rising temperatures, do not significantly affect returns. These findings underscore the importance for fund managers to prioritize acute and transition risks, particularly acute physical risks, in climate-related investment strategies. This study extends the empirical experience in Chinese climate finance, validates a machine-learning-constructed climate risk dictionary, and provides practical insights for fund managers and regulators. A limitation is the reliance on annual reports, which may not capture real frequency shifts in risk attention.

Keywords: climate risk attention, risk management in investments, fund performance, Chinese financial market, actively managed funds, excess returns.

JEL Classification: M41, C83, L20.

Online supplementary material: Supporting information for this paper is available as online supplementary material at https://doi.org/10.3846/jbem.2026.28069

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1. Introduction

In the 21st century, climate change has emerged as one of the most prominent systemic risks facing humanity (Li et al., 2021), profoundly affecting economic and financial system. Globally, major financial institutions such as BNP Paribas, Citigroup, and Barclays have pledged to mobilize trillions toward sustainable investments, underscoring the transition of climate risks from externalities to priced financial factors. Against this backdrop, and particularly within the rapidly evolving Chinese context, studying how financial markets internalize climate risk becomes imperative.

As the world's largest developing economy, China has established a multi-layered climate governance framework that mandates environmental disclosure and risk management for financial institutions. This policy push has catalyzed significant market developments; for instance, in 2023, there were 479 new green bonds in China, and the issuance scale of new green bonds was about 838.87 billion yuan. By the end of 2023, the cumulative issuance scale of green bonds in China was about 3.62 trillion yuan, highlighting the scale and urgency of integrating climate considerations into finance. Consequently, China's capital markets represent a critical, timely setting to examine the shift from policy-driven climate risk management to market-based pricing mechanisms.

While existing literature has explored the impact of climate risk on corporate asset pricing (Barnett et al., 2020; Giglio et al., 2021) and debated whether ESG investments generate excess returns—with mixed conclusions (Auer, 2016; Kreander et al., 2005; Trinks & Scholtens, 2017)—a significant gap remains. Specifically, prior studies often rely on ESG ratings that may not accurately capture investors' subjective attention to climate risk, and their findings are seldom extended to the fund level, especially in emerging markets. Recent efforts to develop universal climate risk indicators, such as those based on corporate communication texts (Li et al., 2024a; Sautner et al., 2023), have yet to be systematically applied to Chinese actively managed funds. These funds, despite being guided by national "Green financial" policies, lack empirical evidence on how their climate risk attention translates into performance. Therefore, this study aims to address the following specific research questions: How does fund-level attention to acute physical, chronic physical, and transition risks differentially affect fund excess returns? Moreover, through what mechanisms do these effects operate?

To answer these questions, this study constructs a localized climate risk indicator for Chinese funds. Building on the textual analysis methods of Sautner et al. (2023) and Li et al. (2024a), we employ a Word2Vec model to develop a Chinese climate risk dictionary from corporate annual reports, extending the measurement from firms to fund holdings. Our empirical strategy is threefold: First, we measure Carhart four-factor model as the primary measure of fund excess returns and the Fama-French three-factor model for robustness checks. Second, we employ multidimensional panel regressions with fund and time fixed effects to examine the impacts of climate risk attention on fund excess return, supplemented by alternative explained variable, considering the omitted variables, and adopting the instrumental variable method to test the robustness. Third, we utilize the Brinson attribution model to decompose the sources of excess returns, thereby uncovering the pathways through which climate risk attention affects performance.

Our findings reveal a nuanced picture. A 1% increase in attention to acute physical risks raises fund excess returns by 24.675%, whereas the same increase in transition risk attention leads to a 2.746% increase—only about 11% of the acute risk effect. Attention to chronic physical risks shows no significant impact. Further decomposition indicates that while chronic physical risks boost return from allocation effect, it undermines stock selection ability, pointing to potential "hidden indexing" behavior among Chinese funds. Structured funds, in particular, exhibit a weakened capacity to benefit from climate risk attention, likely due to herd behavior.

This study makes several contributions to the fields of climate risk attention and investment performance. First, this study extends the work of Sautner et al. (2023) beyond English-language contexts and advance Li et al. (2024a) by applying machine-learning-derived climate risk measures to the fund level in China, offering a novel, context-specific analytical tool. Second, this study provides new evidence from the Chinese market on the climate risk-return nexus, clarifying the heterogeneous effects of risk subtypes and thereby informing the unresolved debate on ESG effectiveness. Third, this study uncovers the dual channels—asset allocation and security selection effects—through which climate risk attention influences performance, offering fresh insights into the asset allocation strategies of funds under climate policy pressures.

The structure of this paper is as follows: Section 2 reviews the literature on climate finance and performance attributions. Section 3 describes the data and construction of the climate risk attention indicator. Section 4 presents the baseline empirical analysis and robustness checks. Section 5 applies the Brinson model to explore transmission mechanisms. Section 6 examines heterogeneity across fund types. Finally, Section 7 concludes with implications for policymakers and investors.

2. Literature review

2.1. Climate risk, ESG investing, and fund performance

2.1.1. Climate risk

Since Nordhaus's (1977) seminal work on the economic effects of climate change, its systemic impacts on business operations (Danese & Marchi, 2024; Hampton et al., 2025), financial systems (Qiao & Chen, 2026; Tao et al., 2026), and real-economy sectors such as agriculture and energy (Cai et al., 2025; Tiwari et al., 2024) have received increasing scholarly attention. In finance, climate change primarily influences investment through two channels: as a physical risk affecting corporate asset pricing (Barnett et al., 2020; Giglio et al., 2021) and as a transition risk influencing investor decisions and asset allocation (Engle et al., 2020). Existing literature has explored measures of climate risk. Methods based on text analysis and machine learning have gained traction. Sautner et al. (2023) employed natural language processing and machine-learning keyword discovery techniques to construct a climate risk dictionary using English corporate conference call transcripts. This text-to-climate measurement approach has been applied in the Chinese context by Guo et al. (2024), who utilized the Word2Vec model to develop a Chinese climate risk disclosure indicator based on social responsibility reports. Other studies have employed different data sources and methods: Hassan et al. (2019) used political and non-political training texts to identify topic-related bigrams, while Mao et al. (2025) adopted Google search volume indices related to climate risk to gauge market attention.

2.1.2. ESG and fund performance

Existing literature has studied ESG funds and their performance. Humphrey et al. (2016) pointed out no differences between ESG funds and traditional funds in performance, while Syed (2017) found that ESG funds only have an advantage in terms of the Sharpe ratio, with no significant difference in the Jensen Index and Treynor Ratio. Some studies examine the impact of China's ESG on fund performance. ESG investments strengthen stock selection ability (Li et al., 2024b) and fund performance (Lin et al., 2025), and fund management companies tend to hold funds with high ESG scores (Liang et al., 2024). But there is a significant gap in the research on the relationship between climate risk attention and fund performance (Li et al., 2024b). Especially, ESG is a broad concept than environment, and it does not only include climate change, but also contains dimensions in society and governance.

Based on previous literature, this study utilizes the Word2Vec method, which is a machine learning-based natural language processing method, to construct a climate risk dictionary through word vector operations. This approach avoids missing synonyms of traditional manually constructed climate risk dictionaries, especially in the Chinese context (Mikolov et al., 2013; Guo et al., 2024).

2.2. Fund performance and attribution models

Previous research has extensively discussed the performance of traditional funds, including Markowitz (1952)'s portfolio theory, Sharpe (1966)'s capital asset pricing model, and the subsequent Sharpe ratio. Scholars generally calculate the excess return with the help of the regression of the econometric model. Jensen (1968) proposed to use the regression intercept α from factor models as a measure of fund excess returns, which is a widely used and accepted method for evaluating fund performance.

Existing literature adopts the T-M quadratic, H-M binomial, and C-L binomial models to investigate fund performance attribution (Treynor & Mazuy, 1966; Chang & Lewellen, 1984; Henriksson & Merton, 1981). In China's market, scholars used Fama and MacBeth method (Yu et al., 2022), excess annualized return (He et al., 2025), Fama-French three factor alpha (Zhang et al., 2024), Carhart four-factor alpha (Han et al., 2024), and Fama–French three-factor and five-factor model (Liu & Yi, 2024) to measure fund excess returns. Currently, Zhao et al. (2016) posited that the RMW and CMA factors of the Fama-French five-factor model had weaker explanatory power for stock portfolios in the Chinese market than the three- and four-factor models. Therefore, this study adopts the performance decomposition method proposed by Brinson et al. (1991) to assess China's investment structure through attribution analysis.

In fund market research, other detailed influencing factors have also been gradually identified, such as fund characteristics and the personal traits of fund managers (Ferris & Yan, 2007; Chevalier & Ellison, 1999), the macroeconomic environment (Baker et al., 2016), and asset allocation strategies (Brinson et al., 1986; Ibbotson & Kaplan, 2000). This study also incorporates significant factors from the Chinese market as control variables.

Overall, existing literature extensively investigates climate change and fund performance. But few studies discuss the relationship between climate risk attention and fund excess returns. This study focuses on this nexus in China's market, which enriches the literature on climate risk attention affecting fund excess returns.

3. Sample and data

3.1. Corporate and fund data

At the corporate level, annual reports of China's A-share listed companies from 2003 to 2023 were scraped from the Giant Tide Information Network. Python-based image recognition, text extraction, and word segmentation yielded 58,508 analyzable text segments. Unreadable reports or those with extraction failures were treated as missing. This text forms the basis for firm-level climate risk indicators. At the fund level, holdings and net asset value data for 435 open-end actively managed equity funds (34,254 annual records) came from the East Money Choice Database. The following cleaning steps were applied: (1) passive funds, index funds, and funds without regular holding disclosures were excluded. (2) Only funds with top-10 holdings constituting at least 40% of total net asset value in a given year were retained, a common threshold to capture core risk exposures. (3) Funds with less than ten years of operating history were excluded to ensure sufficient time-series data. (4) Qualified Domestic Institutional Investor and umbrella funds were excluded due to their distinct mandates. Our reliance on annual reports is grounded in Chinese regulatory evolution: since late 2010, the China Securities Regulatory Commission has required environmental disclosure for specific listed companies, and the April 2024 "Guidelines for Sustainable Development Reports" mandates climate-related disclosure. Even before these mandates, about one-third of

A-share firms voluntarily referenced the Task Force on Climate-related Financial Disclosures framework. Thus, annual reports provide a consistent, policy-anchored source for measuring corporate climate risk exposure, which we map to fund portfolios. For excess return analysis, we follow Jiang et al. (2011), using net asset value and prior-year performance as controls for scale effects and performance persistence.

3.2. Climate risk disclosure index construction

3.2.1. Climate risk dictionary based on unsupervised learning

To account for the distinct financial impacts of climate risks over varying time horizons, this study follows the established literature in distinguishing between physical and transitional risks (Giglio et al., 2021). We further refine this classification into three specific subcategories: acute physical risk (e.g., floods, storms), chronic physical risk (e.g., global warming), and transition risk (e.g., policy shifts, technological disruption, and market changes). This tripartite framework allows for a more granular analysis and helps avoid the biases inherent in a single-perspective approach. Given the unique linguistic characteristics and specific climatic context of China, directly translating dictionaries developed for English-language contexts (e.g., Sautner et al., 2023; Li et al., 2024a) is inadequate. Therefore, this study constructed a tailored Chinese climate risk dictionary using a machine-learning-assisted, iterative methodology. Our approach, similar to Guo et al. (2024), adopts "seed words + Word2Vec" model. Word2Vec is a neural network model that learns word embeddings by analyzing contextual co-occurrence in large text corpora. Its primary advantage is the ability to identify semantically similar words (e.g., discerning that "暴雨" [heavy rain] and "雨灾" [rainstorm disaster] are closely related) without relying on manually engineered features, thereby enhancing the dictionary's coverage and applicability (Mikolov et al., 2013). The dictionary construction followed a rigorous, multi-step process: first, we began with a carefully curated set of seed terms[1] derived from key Chinese climate policy documents and academic literature to ground the model in domain-specific language. Then, a Word2Vec model was trained on our corpus of 58,508 annual report text segments. The training set includes China Climate bulletin, CDP Chinese report, Wikipedia BFS search results, Chinese university textbooks, enterprise environment report, etc. Using the seed words, the model identified and proposed semantically similar candidate terms from the corpus. The Word2Vec model repeat iterations until the ratio of new added candidate terms in dictionary on climate risks less than 5%. Next, the expanded list of candidate terms underwent multiple rounds of manual review and filtering by the research team to ensure precision and relevance. For ambiguous words that the mates in research team have inconsistent opinions, we adopted ChatGPT to judge the accuracy. Finally, to ensure that the identified climate terms reflect genuine discussions of risk rather than neutral descriptions, we implemented a context window filter. A climate term is only counted as a valid indicator of risk exposure if it appears within a 50-word window of at least one term from a separately constructed, general financial and operational risk dictionary (comprising 1,823 terms built using the same Word2Vec method). The 50-word window is a standard choice in financial text analysis for capturing proximate semantic relationships (Hassan et al., 2019)[2]. The final validated dictionary comprises 921 climate risk keywords, clearly categorized into acute physical (180 keywords), chronic physical (228 keywords), and transition risks (513 keywords).

[1] The detailed seed words are listed in Supplementary material.

[2] We validated this choice empirically by conducting sensitivity analyses with alternative windows of 25 and 100 words. The results for robustness checks are reported in Table A1, which confirm the stability of our approach.

Example terms and their contextual usage in annual reports are presented in Table 1, which also reports term frequencies to illustrate the prevalence of different risk discourses in the Chinese corporate context.

Table 1. Climate risk types and frequency of keywords

Acute Physical Risks		Chronic Physical Risks		Transition Risks	
Keyword	Frequency	Keyword	Frequency	Keyword	Frequency
tornado	162,236	hot season	176,019	high-quality development	463,850
heavy snow	45,505	wind speed change	32,658	efficient energy use	417,569
heatwave	6,641	wind speed	31,682	wind energy conversion	294,653
hot weather	6,472	wind direction	20,854	wind power generation	260,561
snowstorm	2,906	strong wind	19,454	wind energy use	198,835
rainstorm	2,243	wind force	15,888	wind energy	173,999
hurricane	2,127	wind	14,904	wind power technology	126,239
wind speed	1,985	illegal logging	12,679	wind farm	125,427
storm surge	1,610	illegal fishing	10,543	wind power	115,987
storm	1,420	illegal mining	9,228	wind energy	109,005
earthquake disaster	1,224	thunderstorm	7,607	wind battery	90,135
shock wave	1,047	raindrop	7,470	wind electricity	84,068
vibration	895	rainwater	6,015	wind power equipment	81,094
hail disaster	826	rain	4,886	wind power system	76,125
hailstorm	808	rainfall	4,880	wind power station	56,837
thunderstorm	799	precipitation variability	4,132	wind turbine	56,475
snowstorm	785	precipitation fluctuation	3,790	wind power industry	55,642
flood disaster	775	precipitation change	3,209	wind power generation	43,759
wildfire	757	precipitation variation	3,197	non-renewable energy	32,054
catastrophe insurance	757	rainfall volatility	3,197	zero carbon emissions	30,263

Notes: This table reports the top 20 most frequent words in different climate risk dictionaries from 2013 to 2023. The complete climate risk dictionary will be provided in Supplementary material.

3.2.2. Measuring climate risk exposure

This study first utilizes the risk disclosure dictionary to measure firm-level climate risk disclosure data, and then transforms these data through the fund's holdings, assessing fund managers' attention to climate risk. Following the approaches of Hassan et al. (2019) and Li et al. (2024a), climate change exposure was defined as follows:

$$CCExposure_{i,t}^{kind,Firm} = \frac{1}{W_{i,t}} \sum_{w}^{W_{i,t}} (1[w \in C]), \quad (1)$$

where $w = 0,1,2 \cdots, W_{i,t}$ represents individual semantic words in company i's annual report in year t, and $1[\cdot]$ is the indicator function that determines whether the word belongs to one of the three climate risk dictionaries: $\mathbb{C}^{acute}$ (acute physical risk), $\mathbb{C}^{chronic}$ (chronic physical risk), or $\mathbb{C}^{transition}$ (transition risk). This gives us the proportion of each firm's annual report discussing climate risk exposure, separated into acute, chronic, and transition risks.

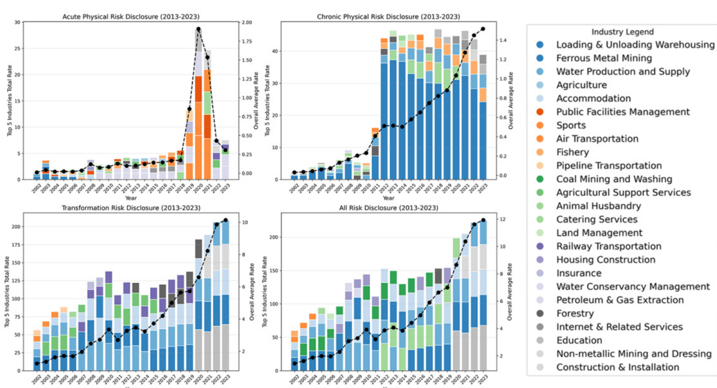
To translate firm-level data into fund-level data, we aggregate it using the weight of holdings. Specifically,

$$CCExposure_{j,t}^{kind,Fund} = \sum_{i} \omega_{i,t} \cdot CCExposure_{i,t}^{kind,Firm}, \tag{2}$$

where $\omega_{i,t}$ is the weight of the stock's value in the fund's total net asset value. As previously stated, this study utilizes the annual reports of open-ended active management funds to identify the top 10 holdings. Excluding funds with the top 10 holdings representing less than 40% of the total value, this study calculates the weighted average of the climate disclosure data of these holdings to measure fund managers' attention to climate risk.

3.2.3. Characteristics of climate risk attention

Climate risk attention by Chinese listed companies shows clear temporal and sectoral heterogeneity (Figure 1). Acute physical risk attention follows an event-driven pattern. The utilities sector saw a pronounced spike in disclosure intensity during the COVID-19 pandemic, a trend also observed in public transportation and education. Chronic physical risk disclosures are most common in sectors directly exposed to environmental changes, such as agriculture, forestry, animal husbandry, fishing, and water-intensive industries like timber processing and power generation. Transition risk attention has historically been concentrated in traditional high-emission sectors (coal, electricity, natural gas). However, a recent notable trend is its expansion into emerging industries such as photovoltaics and new energy technologies. This shift aligns with China's evolving policy landscape, including the amended Renewable Energy Law and the strategic directives of the 14th Five-Year Plan, indicating that transition risk is becoming a relevant framework for assessing both incumbent challenges and new growth sectors. For investment strategies, this means a fund's attention to transition risks must evolve beyond traditional "brown" industries to also encompass the opportunities and vulnerabilities within the "green" transition itself.



Notes: This figure displays the time series characteristics of climate risk disclosure rates for Chinese enterprises. The definition of the climate risk disclosure rate (CCExposure) will be provided later. The bar chart shows the average disclosure rate of the top five industries with the highest risk disclosure rates each year. The industry classification is based on CSMAR, and the average is calculated after computing the disclosure rate for each individual company. The left axis represents the values for the top five industries. The line in the figure represents the average climate risk disclosure rate for all industries, calculated as the average disclosure rate for all A-share listed companies in that year.

Figure 1. Climate risk disclosure industry and time series characteristics of Chinese enterprises

3.3. Measuring fund excess returns

Explanatory power of the Fama-French five-factor model's RMW and CMA factors is weaker in the Chinese market (Zhao et al., 2016). Therefore, this study uses the Carhart four-factor model to assess excess fund returns. The following model was constructed for this study.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i1}MKT_t + \beta_{i2}SMB_t + \beta_{i3}HML_t + \beta_{i4}UMD_t + \mu_{i,t}; \tag{3}$$

$$Carhart_{Alpha_{i,\tilde{t}}} = \alpha_i, \tag{4}$$

where: MKT, SMB, HML, and UMD are the market, size, value, and momentum factors, respectively. t and $\tilde{t}$ are time identifiers for monthly and annual data. We use data from the CSMAR database for the monthly factor data, where UMD is constructed using data from the past 52 weeks, and the four factors are weighed using the free-float market capitalization of all A-shares. Using this method, we calculate $Carhart\_Alpha_{i,\tilde{t}}$ to represent the excess return obtained by fund i in year $\tilde{t}$.

3.4. Control variables

Additionally, we incorporate control variables related to fund performance, such as fund size ($SIZE_{i,t}$), historical performance ($PERF_{i,t}$), and other fund manager-related factors. Following the definition in Chen et al. (2004), we measure fund size as the natural logarithm of total net assets, where $TNA_{i,t}$ denotes the total net assets of fund i at time t:

$$SIZE_{i,t} = \ln\left(TNA_{i,t}\right). \tag{5}$$

To account for the persistent impact of past fund performance, we use the fund's Jensen's alpha from the previous period as a proxy for historical performance, where $Jensen_Alpha_{i,t-1}$ denotes the Jensen's alpha of fund i in the preceding year. Table 2 presents descriptive statistics for the relevant variables:

$$PERF_{i,t-1} = Jensen\,Alpha_{i,t-1}. \tag{6}$$

Table 2. Descriptive statistics

	Count	Mean	Sd	Min	Max
CCE Overall	2801	0.05	0.04	0.000	0.408
CCE Acute	2801	0.00	0.01	0.000	0.045
CCE chronic	2801	0.01	0.00	0.000	0.059
CCE Transition	2801	0.04	0.04	0.000	0.377
Carhart_Alpha	2801	0.19	1.32	–5.693	7.836
Size	2801	10.44	1.72	2.963	15.060
PERF	2801	44.14	28.15	0.000	99.961

Notes: This table reports the summary statistics of all variables used in the regression analysis. All variables are at the fund-year level. The construction methods for the climate risk disclosure index, including variables for acute physical risk, chronic physical risk, and transition risk, have been explained earlier in the text.

4. Climate risk attention and fund excess returns

4.1. Model design: panel data regression

The heterogeneity and cyclical sensitivity inherent in Chinese public funds affect the results of fund-style drift on performance, as inspired by Chen and Wei (2025). This study adopts a two-way fixed effect model to examine the impact of climate risk attention on fund excess returns. The model is structured as follows:

$$Carhart_{Alpha_{i,t}} = \alpha + \beta_1 CCExposure_{i,t}^{kind} + \beta_2 SIZE_{i,t} + \beta_3 PERF_{i,t-1} + \\ + Time_{Effects} + Entity_{Effects} + \mu_{i,t}, \tag{7}$$

where $CCExposure_{i,t}^{kind}$ covers four types of climate risk attention, with $kind$ representing one of the categories: acute physical risk, chronic physical risk, transition risk, and overall disclosure. $SIZE$ denotes fund size, and $PERF$ represents historical performance. $Time\_Effects$ denotes time fixed effects, $Entity\_Effects$ represents individual fixed effects, and $\mu_{i,t}$ is the random fixed effects. Our interest, β_1, denotes the impacts of climate risk attention on fund excess returns. A positive β_1 denotes that climate risk attention promotes fund excess returns; a negative β_1 represents that climate risk attention hinders fund excess returns; and an insignificant β_1 presents climate risk attention cannot affect fund excess returns.

4.2. Baseline results

This study adopts data from 435 funds during 2013–2023 and uses Eq. (7) to examine the impact of climate risk attention on excess fund returns. The results are presented in Table 3.

As shown in Table 3, fund climate risk attention (CCExposure) significantly impacts excess returns and exhibits strong heterogeneity. After decomposing climate risks by type, we found that the coefficient for acute physical risk was 24.675, significant at the 1% level, indicating that a 1% increase in acute physical risk attention leads to 24.675% increases in fund excess returns. This may be due to the funds' ability to assess acute risks and make informed judgments, effectively arbitraging during market volatility. In contrast, the coefficient for transition risk is 2.746, indicating a 1% increase in transition risk attention leads to 2.746% increases in fund excess returns. It means a positive but weaker excess return, possibly linked to China's supportive policies in transition-sensitive sectors, such as new energy. It shows that policy-driven climate risks also have a positive pricing effect, but their economic significance is only 11% of that for acute risks. The coefficient for chronic physical risk, however, is not significant. This finding contrasts with studies in more mature markets (e.g., Giglio et al., 2021) and can be attributed to the unique institutional and behavioral context of China's financial system. On the one hand, the long-term and diffuse nature of chronic risks conflicts with the relatively short performance horizon and high turnover prevalent among many Chinese fund investors, discouraging managers from pricing in decades-long environmental shifts. On the other hand, and more critically, high policy uncertainty dominates the investment landscape. Top-down, implementation-heavy climate policies in China often focus on medium-term transition targets or post-disaster responses, creating clear signals for acute and transition risks. In contrast, consistent, long-term regulatory frameworks for adapting to chronic physical impacts—such as detailed zoning rules, resilience standards, or compensation mechanisms—remain underdeveloped or inconsistently enforced. This policy ambiguity makes it difficult for funds to quantify and price chronic risks into current asset values, as the eventual financial implications for firms are highly uncertain. Consequently, fund managers may rationally ignore these risks in their stock-selection models, leading to the observed statistical insignificance. This insight will be further explored in subsequent mechanism and heterogeneity analyses. The adjusted R^2 for the regression model is approximately 12%, which is consistent with the typical results of Jensen's original study on fund excess returns. The limited explanatory power is mainly due to unobservable active management factors that influence fund alphas. A Hausman test (p-value < 0.01) rejects the random effects hypothesis; thus, a two-way fixed effects model was used to mitigate estimation bias.

4.3. Robustness checks

This study adopts three methods to examine the robustness of climate risk attention on fund excess returns. First, this study employs the alternative explained variable. The Fama-French three-factor model has significant explanatory power for fund excess returns in Chinese fund market. Based on this, this study uses the three-factor model for robustness checks (in Panel A in Table 4). Second, considering that the omitted variables possibly cause a bias estimation for the impacts of climate risk attention on fund excess returns, this study added controls, including manager changes, fund scales, shifts in investment styles, and fee ratios. The related results are in Panel B in Table 4. Third, considering possible endogeneity from bi-directional causal relationships between climate risk attention and fund excess returns, this study adopts instrumental variables to reduce this effect. This study employes the lag period of climate risk attention as the instrumental variables of climate risk and reports the results in Panel C in Table 4. The test results in Table 4 further confirm that the main conclusions hold steady under different risk factor frameworks.

Table 3. Baseline results

	(1)	(2)	(3)	(4)
	Carhart Alpha			
CCE Overall	2.734^{***}			
	(2.77)			
CCE Acute		24.675^{***}		
		(3.34)		
CCE Chronic			7.678	
			(0.77)	
CCE Transition				2.746^{**}
				(2.58)
Size	0.141^{***}	0.138^{***}	0.140^{***}	0.141^{***}
	(5.09)	(4.98)	(5.05)	(5.10)
PERF	–0.000	–0.000	–0.000	–0.000
	(–0.20)	(–0.09)	(–0.32)	(–0.21)
Time Effects	Yes	Yes	Yes	Yes
Entity Effects	Yes	Yes	Yes	Yes
N	2801	2801	2801	2801
R^2	0.261	0.262	0.259	0.261
adj. R^2	0.120	0.121	0.118	0.120

Notes: This table reports the regression results of fund excess returns (Carhart Alpha) on fund climate risk attention (CCExposure). The t-statistics are shown in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4. Robustness checks

	(1)	(2)	(3)	(4)
Panel A: Alternative dependent variable				
Dependent variable: Fama-French Alpha				
CCE Overall	2.367^{***}			
	(2.83)			
CCE Acute		37.512^{***}		
		(6.03)		
CCE Chronic			2.715	
			(0.32)	
CCE Transition				2.211^{**}
				(2.45)
Controls	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes
Entity Effects	Yes	Yes	Yes	Yes
N	2801	2801	2801	2801
R^2	0.366	0.373	0.364	0.365
adj. R^2	0.245	0.254	0.242	0.244
	(5)	(6)	(7)	(8)
Panel B: Adding controls				
Dependent variable: Carhart Alpha				
CCE Overall	2.701^{***}			
	(2.73)			
CCE Acute		24.901^{***}		
		(3.37)		
CCE Chronic			7.480	
			(0.75)	
CCE Transition				2.709^{**}
				(2.54)
Controls	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes
Entity Effects	Yes	Yes	Yes	Yes
N	2801	2801	2801	2801
R^2	0.262	0.263	0.259	0.261
adj. R^2	0.120	0.121	0.117	0.119
	(9)	(10)	(11)	(12)
Panel C: Instrumental variable method				
Dependent variable: Carhart Alpha				
CCE Overall	3.108			
	(0.32)			
CCE Acute		15.205		
		(0.19)		
CCE Chronic			44.709	
			(0.46)	
CCE Transition				7.030
				(0.66)
Controls	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes
Entity Effects	Yes	Yes	Yes	Yes
N	2361	2361	2361	2361

Notes: This table reports the regression results of fund excess returns (Fama-French Alpha) on fund climate risk attention (CCExposure) measured through the three-factor model. The t-statistics are shown in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5. Mechanism analysis of fund performance

5.1. Brinson performance attribution model

Given the unique institutional context and evolving efficiency of the Chinese securities market, this study employs the Brinson performance model. Compared to timing-oriented models like Treynor-Mazuy (T-M) and Henriksson-Merton (H-M), the Brinson model offers a more intuitive and direct decomposition of excess returns into decisions related to asset allocation and security selection. This is particularly suited for analyzing how a fund manager's attention to climate risks translates into performance through these two distinct channels.

Following the standard Brinson framework, the total excess return of a fund portfolio (P) relative to a benchmark portfolio (B) can be decomposed into three components: the allocation effect (A), the selection effect (S), and the interaction effect (I). Formally, for a set of n fund:

The total excess return is:

$$excess\ return = \sum_{i=1}^{n}\left(W_{pi} \times R_{pi}\right) - \sum_{i=1}^{n}\left(W_{bi} \times R_{bi}\right). \tag{8}$$

This can be decomposed as:

$$allocation\ effect\left(A\right) = \sum_{i=1}^{n}\left(W_{pi} - W_{bi}\right) \times R_{bi}; \tag{9}$$

$$selection\ effect\left(S\right) = \sum_{i=1}^{n} W_{bi} \times \left(R_{pi} - R_{bi}\right); \tag{10}$$

$$Interaction\ effect\left(I\right) = \sum_{i=1}^{n}\left(W_{pi} - W_{bi}\right) \times \left(R_{pi} - R_{bi}\right), \tag{11}$$

where W_{pi} and W_{bi} are the portfolio weight and benchmark weight for fund i, respectively. R_{pi} and R_{bi} are the return of the portfolio's holdings in fund i and the return of the benchmark in fund i, respectively. $excess\ return = A + S + I$.

In the context of climate risk attention, a significant allocation effect would indicate that managers generate excess returns by overweighting (or underweighting) funds that are differentially exposed to or resilient against specific climate risks. A significant selection effect would indicate an ability to pick winning stocks within sectors based on firm-level climate risk management or exposure. The interaction effect captures the combined effect of market timing and stock picking. Following this framework, we decomposed each fund's annual performance, as shown in Table 5.

This study uses the top ten holdings and their respective weight data disclosed in annual reports. Funds with the top ten holdings comprising less than 40% of the portfolio and those primarily investing in Hong Kong stocks are excluded from the analysis. The weights are normalized based on the portfolio's holdings. This study uses an annual holding period for the fund with asset ratios disclosed at the end of each period. As the specific stock holdings during the period cannot be accurately obtained, we assume that the fund adjusts its portfolio at the beginning of the year and maintains the same allocation until the end of the period. This assumption reflects the fund manager's portfolio adjustments after considering climate risk disclosures, which are more accurate than using the end data of the previous period as the current period's starting position. Based on this idea, annual-level performance decomposition data were constructed. The main reasons as follow: 1) The primary source of climate risk attention data is corporate annual reports, making annual holdings data the most consistent and reliable match; and 2) Chinese active equity funds are typically evaluated against annual performance benchmarks, and their strategic asset allocation decisions are often calibrated to yearly investment themes and policy cycles, making the annual horizon most relevant for assessing the implementation of climate-aware strategies.

Table 5. fund performance decomposition based on the brinson model

Effect	General Formula	Interpretation in Climate Context	Hypothetical Example
Allo-cation (A)	$\Sigma\left(W_{pi}-W_{bi}\right)\times R_{bi}$	Return from deviating benchmark weights in climate-relevant fund.	Fund overweight: $W_{pi}=12\%$, $W_{bi}=8\%$. Benchmark return $R_{bi}=10\%$. Contribution: (0.12 – 0.08) × 0.10 = 0.4%.
Selec-tion (S)	$\Sigma W_{bi}\times\left(R_{pi}-R_{bi}\right)$	Return from picking better-performing stocks within funds, potentially based on firm-level climate resilience.	Benchmark weight $W_{bi}=8\%$. Fund's stocks in sector return $R_{pi}=15\%$. Contribution: $0.08\times\left(0.15-0.10\right)=0.4\%$.
Inter-action (I)	$\Sigma\left(W_{pi}-W_{bi}\right)\times\left(R_{pi}-R_{bi}\right)$	Joint effect from both overweighting a fund and outperforming within it.	Using above data: $\left(0.12-0.08\right)\times\left(0.15-0.10\right)=0.2\%$.
Total Excess	$\Sigma W_{pi}R_{pi}-\Sigma W_{bi}R_{bi}$	Total outperformance attributable to the manager's decisions.	Sum of contributions: $0.4\%+0.4\%+0.2\%=1.0\%$.

Notes: This table presents the Brinson model for performance attribution of funds. It shows the calculation method for a specific type of return effect in a given year for a single fund. Considering that climate risk attention can alter the fund manager's selection of sectors and individual stocks, W_{bi} and W_{pi} represent the market value weights of the sector i in the All-A Index and the fund's weight in the corresponding sector, respectively. R_{bi} and R_{pi} represent the benchmark sector return and the fund's sector return, respectively.

5.2. Mechanism test: How climate risk disclosure affects fund performance

Following the annual performance decomposition using the Brinson model, we examine the specific channels through which climate risk attention affects fund excess returns. We estimate the following regression model:

$$Effect_{i,t}=\alpha+\beta_1 CCExposure_{i,t}^{kind}+Time_{Effects}+Entity_{Effects}+\mu_{i,t},\qquad(12)$$

where $Effect_{i,t}$ refers to one of the three Brinson components (asset allocation, security selection, or interaction effects) for fund i in year t.This study controls individual and year fixed effects. Table 6 presents the results.

The results reveal that the performance impact of climate risk attention is channel-specific and varies significantly by risk type. Attention to acute physical risks significantly boosts the interaction effect $(\beta=4.029,\ p<0.05)$, while negatively affecting both allocation $(\beta=-2.652,\ p<0.1)$ and selection $(\beta=-9.357,\ p<0.01)$. This pattern suggests that funds do not generate alpha by simply overweighting exposed sectors or by picking resilient stocks within sectors. Instead, excess returns stem from the synergistic, contrarian strategy captured by the interaction term. We interpret this as funds identifying sectors and firms that are oversold due to short-term climate shocks. By simultaneously increasing exposure to the distressed sector and selecting specific oversold stocks within it, they capture a rebound premium when the market corrects its overreaction. This mechanism directly explains the positive alpha associated with acute risk attention in Table 3. Attention to both chronic physical and transition risks follow a similar pattern: it significantly increases returns from allocation ($\beta = 14.077$ for chronic risk, $p < 0.01$) but erodes returns from selection ($\beta = -7.990$ for chronic risk, $p < 0.01$). The interaction effect is positive for chronic risk but insignificant for transition risk. This reveals a strategic trade-off. Funds appear to successfully ride policy-driven sector beta, which generates positive allocation returns. However, this herding into popular policy themes comes at the cost of diminished stock-picking alpha. This is likely because managerial resources and research depth are diverted towards top-down sector bets, leading to insufficient scrutiny of firm-specific transition competencies. Consequently, stock selection within these crowded sectors adds little value, generating a return pattern consistent with the "closet indexing" phenomenon observed in other markets (Petajisto, 2013). This dynamic in China's climate-aware investing landscape—where managers may inadvertently or strategically mimic broad sector weights while diluting stock-picking effort—helps explain the net insignificant effect of chronic risk on overall alpha (Table 3): the strong positive allocation gains are effectively offset by weak or negative selection performance.

Table 6. Brinson model attribution with model selection

	Acute Risk	Chronic Risk	Transition Risk	Overall
Allocation Effect				
CCE	–2.6516*	14.0769***	0.6654***	0.5178***
	(–1.7218)	(7.9138)	(4.4263)	(3.6676)
Const	–0.1189***	–0.2309***	–0.1663***	–0.1641***
	(–16.2465)	(–16.6687)	(–16.8966)	(–15.3577)
Hausman χ2	76.7780***			
Model	FE	RE	RE	RE
Selection Effect				
CCE	–9.3565***	–7.9896***	–0.2472**	–0.1893*
	(–4.7874)	(–6.0667)	(–2.0665)	(–1.7008)
Const	0.1152***	0.1291***	0.0856***	0.0846***
	(12.3999)	(11.7632)	(9.9731)	(9.2449)
Hausman χ2	68.0400***	4.2430		0.7725
Model	FE	RE	RE	RE
Interaction Effect				
CCE	4.0293**	3.1841**	–0.1411	–0.0666
	(2.2501)	(2.1372)	(–0.9193)	(–0.4720)
Const	–0.1143***	–0.1176***	–0.0878***	–0.0910***
	(–13.4274)	(–11.1832)	(–10.9568)	(–10.2664)
Hausman χ2	30.2753***	335.2589***	35.5134***	24.9812***
Model	FE	FE	FE	FE

Notes: This table presents the regression results between climate risk attention (CCExposure) and different effect returns from the Brinson model. The t-statistics in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6. Fund heterogeneity: the risk neglect of structured funds

To examine whether the impact of climate risk attention varies across fund structures, this study conducts a heterogeneity analysis using a subsample of structure funds (also known as segmented or leveraged funds). Structured funds are unique investment vehicles that split portfolio into two distinct share classes with differing risk-return profiles: Class A shares (also known as conservative, preferred, or low-risk shares) and Class B shares (also referred to as aggressive, subordinated, or high-risk shares). This structure inherently makes the fund highly sensitive to broad market and systemic risks, as losses are disproportionately borne by B-share holders, creating complex risk-shifting dynamics (Coval et al., 2009). We hypothesize that structured funds, due to their focus on managing this embedded leverage and systemic risk exposure, may be less incentivized to pursue excess returns from non-diversifiable, long-horizon climate risks. Managers might perceive climate risks as difficult to hedge within the fund's leveraged structure and could prioritize short-term volatility management over integrating climate considerations.

The first structured funds in China were launched in 2007. Following the implementation of the New Asset Management Rules and the conclusion of its transition in late 2020, regulatory scrutiny intensified due to concerns over high leverage and complexity. This led to a gradual phase-out of such products, with only a few undergoing transformations by 2025, To account for potential shifts in management strategy during this period, this study classifies structured funds based on whether they experienced a fund manager change after post-2020. If there are no changes in fund managers, this fund is structure fund; and otherwise, the fund is non-structure fund. This study adopts Equation 7 separately to estimate structure and non-structure funds. The results are presented in Table 7. The results reveal significant structural heterogeneity. Non-structured funds show a strong, positive responsiveness to acute physical risks, generating substantial excess returns ($\beta = 31.327$, $p < 0.01$). Similar as baseline results, the coefficients of overall climatic risk attention ($\beta = 2.7701$, $p < 0.05$) and transition risk attention ($\beta = 2.7045$, $p < 0.1$) are significantly positive, aligned with our earlier finding that conventional active managers can arbitrage short-term market dislocations caused by climate shocks.

By contrast, structured funds show no significant relationship between acute risk attention and excess returns. This supports our hypothesis that the embedded leverage and risk-shifting mechanisms inherent to their structure discourage managers from actively engaging with non-diversifiable climate risks. The priority appears to be managing the immediate systemic and volatility risks amplified by leverage, leading to a form of climate risk neglect. For chronic physical and transition risks, the findings are consistent with earlier patterns observed across the full sample, with no significant alpha generation for either fund type, further underscoring the prevalence of policy-driven herding. This finding extends the literature on herding behavior in financial markets. The "closet indexing" phenomenon observed in conventional funds is amplified in structured funds into a more pronounced strategic neglect of complex, long-term risks like climate change.

Table 7. Heterogeneity Test: Grouped Regression Results for Structured Funds

	Carhart Alpha							
	Non-structured	Structured	Non-structured	Structured	Non-structured	Structured	Non-structured	Structured
CCE Overall	2.7701^{**}	1.5055						
	(2.0434)	(0.9373)						
CCE Acute			31.3270^{***}	8.5940				
			(3.1320)	(0.5967)				

End of Table 7

	Carhart Alpha							
	Non-structured	Structured	Non-structured	Structured	Non-structured	Structured	Non-structured	Structured
CCE Chronic					8.4006	0.1679		
					(0.5364)	(0.0118)		
CCE Transition							2.7045*	1.5331
							(1.8641)	(0.8740)
const	–1.5680***	–1.3379**	–1.5468***	–1.3124**	–1.4749***	–1.2826**	–1.5410***	–1.3373**
	(–3.8039)	(–2.1108)	(–3.8001)	(–2.0723)	(–3.5252)	(–2.0310)	(–3.7489)	(–2.1085)
Size	0.1524***	0.1353**	0.1509***	0.1372**	0.1518***	0.1378**	0.1522***	0.1365**
	(3.9376)	(2.2775)	(3.9075)	(2.3110)	(3.9137)	(2.2995)	(3.9328)	(2.2991)
PERF	0.1747	–0.0956	0.1598	–0.1021	0.1862	–0.0953	0.1757	–0.0964
	(1.4691)	(–0.5642)	(1.3450)	(–0.6011)	(1.5659)	(–0.5605)	(1.4774)	(–0.5690)
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Entity Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0201	0.0088	0.0242	0.0081	0.0172	0.0076	0.0195	0.0087
F-statistic	8.9646***	2.0937*	10.8749***	1.9182	7.6463***	1.7987	8.7270***	2.0552
Hausman χ^2	66.0474***	26.4580***	32.9712***	10.9438**	56.5840***	22.6924***	66.1694***	26.4471***

Notes: This table reports the results of the grouped regressions between fund excess returns (Carhart Alpha) and fund climate risk attention (CCExposure) for structured funds. Each pair of columns presents the results for the overall situation, acute physical risk, chronic physical risk, and transition risk, with one column showing the regression results for non-structured funds and the other for structured funds. The same set of fixed effects is used in the regressions. The table also reports the results of the Hausman test to ensure the effective control of year-time fixed effects and fund-entity fixed effects. t-statistics in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

7. Conclusions and Implications

This study constructs a new climate risk attention indicator for Chinese actively managed funds by applying machine-learning-based text analysis to corporate annual reports and aggregating firm-level exposure to fund portfolios. The results show that attention to climate risk significantly influences fund excess returns, but the effects are highly heterogeneous across risk types and transmission channels. Attention to acute physical risks, such as typhoons and floods, generates the most substantial positive alpha, primarily through returns from asset allocation and interaction effects, suggesting funds employ contrarian strategies in impacted industries. In contrast, attention to transition risks, such as carbon policies, has a statistically significant but economically modest effect (only 11% of the acute risk impact), indicating high market pricing efficiency or short-term speculative dynamics for these policy-driven risks. Notably, attention to chronic physical risks, such as rising temperatures, shows no significant effect, likely due to a prevalent “closet indexing” strategy where funds herd into policy-favored sectors, thereby diluting stock selection alpha.

This study makes the following contributions. First, this study develops and validates a localized Chinese climate risk dictionary using a Word2Vec model, providing a replicable framework for non-English markets. Second, this study provides the first direct evidence that Chinese fund managers can translate climate risk attention into excess returns, with an annualized alpha of approximately 2.7% associated with acute risk focus. Third, by applying the Brinson attribution model, we uncover an asset allocation–stock selection paradox: while climate risk attention can enhance sector beta, it may simultaneously erode stock-picking gains, deepening the understanding of performance drivers in emerging markets.

The potential practical implications are primarily twofold. For investors and fund managers, our results highlight the importance of differentiating climate risk subtypes in strategy formulation. Screening funds based on their attention to acute physical risks, rather than broad ESG scores, could identify managers with genuine alpha-generating skills. For investors seeking climate-aware strategies that generate alpha, our results suggest a clear preference for non-structured, actively managed funds. Structured funds, given by their risk profile and managerial incentives, appear ill-suited as vehicles for translating climate risk attention into excess returns. For regulators, accelerating standardization and mandating climate disclosures could enhance market efficiency.

This study has limitations that point to future research. First, reliance on annual fund holding data may underestimate high-frequency pricing effects; using semi-annual or quarterly data could refine the analysis. Second, our firm-level measure does not capture supply-chain-mediated climate risks; integrating input-output tables to construct networked-based exposure indicators would be a valuable extension. Third, the findings are specific to Chinese equity funds; their generalizability to bond funds, mixed products, or other markets requires further validation. Looking forward, the integration of advanced AI and machine learning—such as transformer-based models for contextual semantic analysis and real-time processing of corporate communications—promises to evolve climate dictionaries from static keyword lists into dynamic, adaptive tools. This would enable real-time monitoring of climate risk sentiment and its market impact, opening new frontiers for both academic research and practical risk management. Fourth, while the Brinson model effectively decomposes returns into allocation and selection, it is a static, return-based framework. It does not explicitly account for risk dynamics particularly relevant to climate investing, such as changes in portfolio volatility or tail risk exposure stemming from climate shocks. Future research could extend this analysis by incorporating climate-adjusted risk metrics into the attribution framework or by analyzing the volatility of each performance component. Fifth, future Research could delve deeper into the behavioral and institutional factors driving this neglect, examining how compensation structures, regulatory pressures, and investor redemption patterns in structured funds influence managers' climate risk engagement.

Acknowledgements

The authors would like to thank the editor and anonymous reviewers for their contributions towards improving the quality of this paper.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Author contributions

Kaisheng Yang: Writing – Original Draft, Writing – Review & Editing, Methodology, Formal analysis, Data Curation; Ximan An: Writing – Review & Editing, Investigation.

Disclosure statement

The authors declare that it does not have any known interests or personal relationships that could potentially influence the reported work in this paper.

Data availability statement

The authors will supply the relevant data in response to reasonable requests.

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