Hedge Funds and ESG Sentiment

Bing Liang* and Jue Wang†‡

Abstract

This paper examines whether hedge funds capitalize on fluctuations in ESG sentiment. Using a novel global dataset of public ESG perceptions, we construct composite and pillar-level sentiment indices. We find that hedge funds actively time ESG sentiment, exploiting short-term lags to generate higher alpha and reduce downside risk. Timing ability varies across strategies, with directional and semi-directional funds showing the strongest performance. Pillar-level timing aligns with fund focus: environmental timing is most effective in resource-intensive sectors and green regions; social timing benefits stakeholder-oriented strategies; and governance timing is strongest among fixed-income and event-driven strategies that are sensitive to management quality. Overall, the results show that hedge funds can incorporate public, values-based ESG perceptions into return generation and risk management.

JEL Classification: G23, Q51, Q56, P28, E32

Keywords: Sentiment Trading; Market Timing; Fund Manager Skills; Hedge Funds; Sustainability; ESG; Machine Learning

* University of Massachusetts Amherst, 121 Presidents Drive, Amherst, MA 01003, bliang@isenberg.umass.edu.
† Yale University, 165 Whitney Ave, New Haven, CT 06511, jue.wang@yale.edu; University of Massachusetts Amherst, 121 Presidents Drive, Amherst, MA 01003, juewang@umass.edu.
‡ We sincerely appreciate Fousseni Chabi-Yo, Christoph Bauner, Karim Farroukh (discussant), William N. Goetzmann, Allaudeen Hameed, Theis Ingerslev Jensen, Adam T. Jørring, Hossein Kazemi, Wenting Ma, Marco Macchiavelli, Anya Mkrtchyan, Neil Pearson, Alp Simsek, Mila Getmansky Sherman, Matthew Spiegel, and seminar participants at the 2025 FMA Doctoral Student Consortium, 2025 FMA New Ideas Session, The Friends of Women in Finance 4th Symposium in Greater New York, 6th Annual RCF-ECGI Conference, Bryant University, California State University, Northridge, Hofstra University, Monash University, University of Massachusetts Amherst, and Yale University for their helpful comments and suggestions.

"Let it be a season in which we make a long overdue investment in the survival and security of future generations."[1]

Kofi Annan (Former UN Secretary-General)

1. Introduction

There has been growing attention to ESG-related discussions in financial markets. Beyond general public attention, ESG sentiment has been shown to influence asset prices and hedging outcomes (de Franco, 2020; Engle et al., 2020; Serafeim, 2020; Pastor et al., 2021; Ardia et al., 2023). Hedge funds, among the most sophisticated market participants, actively employ ESG-related stock selection and factor exposures to enhance performance and manage risk (Liang et al., 2022; Ardia et al., 2024; Kuang et al., 2024). Prior studies also document their superior market-timing ability under profitability-driven conditions (Chen and Liang, 2007; Cao et al., 2013; Chen et al., 2021). This evidence raises a natural question: can hedge funds strategically time ESG sentiment—a values-based market signal—to generate alpha and mitigate risk?

This paper examines their timing ability across the environmental, social, and governance (ESG) pillars. Specifically, we study whether and how hedge funds can time the trajectories of ESG sentiment to achieve performance enhancement and risk mitigation. To capture timely and comprehensive ESG sentiment, we use the LSEG MarketPsych ESG Analytics dataset, which measures firm-level ESG sentiment from news and social media in

[1] https://www.un.org/sg/en/content/sg/speeches/2002-09-03/secretary-general-kofi-annan-world-summit-sustainable-development.

near real time using advanced natural language processing. This high-frequency dataset provides granular insights into worldwide public perceptions of firms' ESG practices. Since hedge funds typically respond to aggregate signals rather than firm-specific news (Chen et al., 2021; Caglayan et al., 2024), we aggregate firm-level metrics and construct a composite ESG sentiment index and pillar-level indices (Environmental, Social, and Governance) using Principal Component Analysis (PCA) to capture the dominant variations in market sentiment.

We find that hedge funds can time the major trajectories of ESG sentiment, particularly along the environmental and social pillars. Nearly 40% of funds exhibit significant exposures to at least one ESG pillar, and among these, over 65% display significant timing skills. Directional and semi-directional funds, which are more willing to take market risks, show larger exposures to ESG sentiment and substantially stronger timing ability. For funds with significant exposures and timing ability, average environmental exposures reach 0.47, with timing ability of 0.58, while average social exposures reach 0.42, with timing ability of 0.60. These findings indicate that directional and semi-directional funds not only tilt to high ESG sentiment stocks but also dynamically adjust their exposures effectively, demonstrating superior timing ability.

Furthermore, funds with stronger ESG timing skills experience performance and risk-mitigation benefits. Higher ESG timing ability is associated with increased alpha—up to 24 (E) and 25 (S) basis points cross-sectionally—and lower downside tail risk. Funds with superior pillar-level timing also attract additional fund flows, even during the COVID-19 recession period, suggesting that investors value funds' ESG sentiment timing ability.

Moreover, we explore the mechanism underlying these timing strategies. Specifically, we investigate how hedge funds adjust their stock holdings in response to changes in pillar-level sentiment. We find that funds increase long positions in stocks with higher ESG pillar sentiment one quarter before a market-level sentiment rise above its 36-month rolling average. These results suggest that hedge funds do not passively follow sentiment trends but anticipate future changes, indicating proactive sentiment timing behavior.

One potential explanation for this finding is that hedge funds exploit temporary mispricing when there is a lag between shifts in ESG sentiment and corresponding stock price adjustments. Examining the cumulative abnormal returns (CARs) of stocks with the top 20% increases or decreases in sentiment, we find that price reactions occur with delayed lags, implying that sentiment changes precede price adjustments. This provides evidence that hedge funds time ESG sentiment to capture short-term mispricing opportunities arising from the delay between public perception shifts and price realizations.

Finally, we examine the determinants of hedge funds' ESG timing abilities. Funds allocating assets in Western Europe with greater exposure to soft commodities and the shipping sector, which are more sensitive to environmental policies, exhibit stronger environmental timing skills. Funds with exposure to healthcare and socially responsible investment mandates demonstrate higher social timing abilities, while those focusing on corporate bonds and distressed assets show stronger governance timing skills.

Our paper contributes to three strands of literature. First, it extends the hedge fund skill measurement literature by capturing a previously unexplored dimension of timing ability related to ESG sentiment. Prior research documents hedge funds' stock-picking abilities (Griffin and Xu, 2009; Cao et al., 2018a, 2018b; Grinblatt et al., 2020). We complement this literature by identifying a novel dimension of timing skill. Beyond exploiting traditional market conditions (Chen, 2005; Chen and Liang, 2007; Cao et al., 2013) and investor sentiment (Chen et al., 2021), hedge funds can further time market-level ESG sentiment, a belief-based, non-pecuniary signal rooted in public sustainability discussions.

Second, this paper contributes to the literature on institutional investors' ESG engagement. Prior studies examine mutual funds and other mandate-restricted investors' ESG investment behavior and shareholder responses.[2] Recent work shows that hedge funds can attract capital and improve performance through ESG disclosure and greener portfolio tilts (Liang et al., 2022; Aragon et al., 2024; Kuang et al., 2024; Liang et al., 2024). However, the mechanism through which hedge funds utilize ESG market signals to enhance profits remains unclear. Brogger and Kronies (2025) show that flexible investors benefit from shocks in climate-related attention that lead constrained investors to push up the prices of high-ESG stocks. Our findings extend this view by showing that hedge funds predict and trade ahead of changes in market-level ESG sentiment, taking long positions in stocks with rising sentiment before aggregate sentiment shocks occur.

Finally, we contribute to the construction of ESG sentiment indices. Prior work focuses

[2] Sustainable investment outcomes are increasingly studied for mutual funds and pension funds. Clients favor institutions with higher ESG scores (Ceccarelli et al., 2023), and low-carbon funds saw increased demand following the 2018 introduction of carbon risk metrics (Ceccarelli et al., 2024b). Participation in UNPRI and higher ESG ratings further boost fund flows (Kim and Yoon, 2023; Aragon and Chen, 2024). Pension funds leverage long-term horizons to integrate ESG practices (Cornell, 2020; Lachance and Stroehle, 2021).

mainly on environmental sentiment derived from news-based measures (Engle et al., 2020; Serafeim, 2020; Ardia et al., 2023). Moreover, Eskildsen et al. (2024) link expected returns to static ESG measures reflecting firms' fundamental operations. we complement this literature by developing composite and pillar-level sentiment indices that capture near real-time, news- and social media-based perceptions of firms' ESG practices worldwide. These forward-looking indices reflect public's non-pecuniary beliefs that provide exploitable trading signals for sophisticated investors such as hedge funds.

The remainder of the paper is organized as follows. Section 2 describes the data and presents descriptive statistics. Section 3 outlines the construction of ESG sentiment indices. Section 4 measures hedge funds' pillar-level timing skills and examines their implications for performance and risk mitigation. Section 5 investigates the mechanisms underlying hedge funds' proactive pillar timing and the drivers of superior performance. Section 6 presents robustness checks, and Section 7 concludes.

2. Data

2.1 Public Sustainability Sentiment

The first is the LSEG MarketPsych ESG Analytics database, which provides public sustainability sentiment derived from unstructured news and social media content. Using advanced natural language processing (NLP), the database analyzes over 300,000 sources across 13 languages and generates more than 100 ESG-related metrics covering both pecuniary and non-pecuniary issues (Aggarwal et al., 2024). Key features include real-time sentiment measurement at multiple frequencies, source-specific tone analytics, verified entity identification, and advanced linguistic flow analysis.[3]

The database reports 23 directional ESG sentiment scores ranging from −1 to 1, spanning Environmental (7), Social (11), and Governance (5) pillars. These scores capture net sentiment across dimensions such as emissions, environmental innovation, workforce, community, management, and shareholders. The coverage includes 93,378 firms across 173 countries with at least one non-missing ESG sentiment measure.

Sentiment scores are computed as the difference between weighted positive and negative statements, normalized by total mentions (Buzz). For example, Product Sentiment is calculated as (Positive − Negative) / Buzz. We aggregate daily firm-level sentiment to monthly averages to align with hedge fund data from TASS, producing a panel from January 2003 to December 2024.

[Insert Figure 1]

Figures 1A–1C show that ESG sentiment varies systematically across regions, with European, Asia-Pacific, and Australian firms exhibiting higher average sentiment. Panel A of Table 1 presents summary statistics: the Environmental pillar has the highest mean sentiment (0.12) and volatility, the Social pillar shows moderate sentiment with the lowest dispersion, and the Governance pillar has the lowest mean sentiment (−0.01) but relatively high

[3] The LSEG MarketPsych database uses advanced NLP with tone-level analytics across news and social media. It correctly captures contextual sentiment, such as recognizing “Management crushed it!” as positive, and addresses company aliases and spelling variations through manual review. The system weights adjectives, verb tense, and intensity to capture nuance, and to mitigate greenwashing risk, it excludes company-generated content, such as spokesperson quotes, from ESG sentiment measures.

variability.

[Insert Table 1]

2.2 TASS

The second data source in this paper is TASS, which provides information on hedge fund performance, characteristics, asset instruments, and focus details from January 2012 to December 2024. We use funds that report monthly net-of-fee returns and have at least 36 months of return data. Funds with assets under management (AUM) less than $10 million are excluded, and top and bottom 1% return values are winsorized. After cleaning the data, we have 4,557 funds from 1,591 unique firms.[4] Descriptive statistics for the funds' performance and characteristics are presented in Panel B of Table 1.[5]

2.3 Hedge Fund Excess Return and ESG Sentiment Variables

An initial question is to examine the hedge fund excess return exposures to the individual sentiment variables. This can be tested using the following fund-level regression model, presented in Equation (1) below:[6]

---

[4] All non-US domiciled funds' assets under management are converted to US dollars using the annual exchange rates provided by the OECD (https://data.oecd.org/conversion/exchange-rates.htm).
A total of 9,343 funds (1,074 companies) is excluded due to reporting quarterly or gross-of-fee returns or having assets under management (AUM) of less than $10 million. Additionally, 3,727 funds (756 companies) are excluded for having fewer than 36 months of monthly return data.

[5] Table 2 in the Appendix presents the investment approaches, asset allocations, and investment focuses for funds.

[6] $Excess\ Return_t$ is calculated by using a fund's monthly return minus the 3-month US Treasury Bill return at month t. Following the approach of Caglayan et al. (2025), Chu et al. (2024), and Kuang et al. (2024),we test hedge fund exposures to the relevant ESG sentiment variables using a return-based methodology. The excess

$$Excess\ Return_t = \alpha_t + \beta^{Indp}\Delta Sentiment_{tp}^{Ind} + \theta' f_t + \sum_{j=1}^{S_i-1}\gamma_j StyleDummies_j + \sum_{q=1}^{Y_i-1}\eta_q YearDummies_{qi} + \varepsilon_t \quad (1)$$

For each fund i at month t,we regress its excess return on the changes in sentiment variable p ($\Delta Sentiment_{tp}^{Ind}$). The change in sentiment ($\Delta Sentiment_{tp}^{Ind}$) is calculated as the difference between the current and the previous month's sentiment value: $Sentiment_{tp}^{Ind} - Sentiment_{t-1\,p}^{Ind}$. f_t represents the nine hedge fund factors selected by Chen et al. (2025), which include the equity market, asset growth, betting against beta, low-risk, return-on-assets, time-series momentum, monthly changes in the 10-year Treasury yield, monthly changes in credit yield spread, and term spread factors.[7] Y_i and S_i represent the total number of years and styles for fund i.[8] Table 2, Panel A presents the average of β^{Ind} and adjusted R^2 for sentiment variable p across all funds, along with the descending order ranks based on the exposure values.

According to Panel A, hedge funds are significantly influenced by changes in ESG sentiment. Among the 23 individual sentiment variables, over 82.60% (19 out of 23) exhibit a positive correlation with excess returns. The environmental and social pillars rank higher in terms of coefficients, with 5 out of the top 11 variables falling under these pillars. *Customer Satisfaction*, a sentiment variable within the social pillar, stands out as the most popular

return is calculated by subtracting the 3-month US Treasury Bill return from the monthly rate of return. Additionally, we use the changes in sentiment as the main independent variable, as done by Chen et al. (2021).

[7] Weget the data from Yong Chen's website: https://sites.google.com/site/yongchenfinance/.

[8] TASS style and year dummies are included in the regression, along with clustered standard errors for both style and year. This specification is also applied in Equation (4) in Section 4.2.

among hedge funds. This may be attributed to the role of Corporate Social Responsibility (CSR) in reducing capital constraints by mitigating agency costs and information asymmetry (Cheng et al., 2013), as well as lessening agency concerns, such as limited cash reserves and favorable pay-for-performance structures (Ferrell et al., 2016). Similarly, *Trust*, another common CSR-related variable, ranks as the 4th highest sentiment change beta.

[Insert Table 2]

Panels B and C present summary statistics and a relative importance test for pillar-wise analysis. The Environmental pillar ranks the highest in median rank, followed by the social pillar, while Governance variables rank the lowest. Within the Environmental pillar, positive changes in *Airborne Emissions Improvement* and *Sustainability Improvement* show the strongest co-movement with increased excess returns, ranking first and second within the pillar, respectively.

2.4 Hedge Fund Stock Holding Positions

We obtain hedge fund managers' stock holding positions from the LSEG Institutional Holdings (Form 13F) database, which reports quarterly changes in institutional equity holdings. We match the TASS hedge fund universe with the 13F filings and further align stock names and tickers with the ESG sentiment database. This process yields stock-level holdings for 3,492 unique hedge funds—representing a 76.63% matching rate—and includes 15,478 stock-level observations with at least one non-missing net sentiment variable from the MarketPsych dataset.

3. Public ESG Sentiment Index

3.1 Composite and Pillar-wise ESG Sentiment Index

In this section, we construct a unidimensional public ESG sentiment index using Principal Component Analysis (PCA). Following Baker and Wurgler (2006, 2007), we use the first principal component (PC) as the composite ESG sentiment index. As shown in Figure 2, the first PC explains 53.76% of the total variance, indicating that it captures the dominant common variation across ESG sentiment variables.

[Insert Figure 2]

Table 3 reports the PC loadings, rank statistics, and relative importance test results based on median ranks across the three pillars. Rankings are determined by the absolute magnitude of loadings. Among the top 11 variables, six belong to the environmental pillar, which contains only seven variables in total. *Airborne Emission Improvements* and *Sustainability Improvements* rank as the two most important variables, consistent with the hedge fund excess return exposure rankings in Panel A of Table 2. *Workplace Sentiment* and *Trust* remain the two most important social variables, highlighting the importance of relationships between firms and employees, as well as firms and customers. Within the governance pillar, *Accounting Sentiment* maintains the same rank in both Table 3 and Table 2. *Shareholders* emerges as the most important variable based on variance contribution, consistent with Aggarwal et al. (2024), who show that negative ESG-related sentiment increases investor dissatisfaction.

Panels B and C of Table 3 present median rank tests across pillars. Consistent with Table 2, the environmental pillar is more important than the social pillar, which in turn dominates the governance pillar. Moreover, six variables among the top 11 PC loadings in Panel A of Table 3, namely *Airborne Emission Improvements*, *Sustainability Improvements*, *Pollution Improvements*, *Accounting Sentiment*, *Workplace Sentiment*, *Trust*, and *Climate Policy*, also rank among the top 11 in excess return exposure magnitude. These results suggest that hedge funds not only respond to ESG sentiment fluctuations but also exhibit skill in identifying and timing exposure to the dominant drivers of ESG sentiment. Specifically, hedge fund returns are more sensitive to sentiment variables that define the primary dimension of ESG variation, indicating systematic ESG signal processing rather than indiscriminate ESG exposure.

[Insert Table 3]

Using the PC loadings in Table 3, we construct the composite ESG sentiment index. Figure 3 plots the monthly index from 2003 through 2024. The index captures major ESG policy developments, including the UN Sustainable Development Goals in 2012, the ESG Disclosure Simplification Act in 2021, and the European Sustainability Reporting Standards in 2023. It also reflects major ESG-related scandals, such as environmental incidents, governance failures, and data privacy breaches, that significantly shaped public ESG sentiment.

In addition to the composite index, we construct pillar-level sentiment indices using the same PC-based weights. Figure 4A shows that the environmental, social, and governance indices follow distinct trajectories over time, underscoring the value of pillar-level measures for more granular decomposition analyses.

[Insert Figure 4]

4. ESG pillar sentiment timing skills, hedge fund performance benefits, and risk mitigation

4.1 Hedge Fund Pillar Exposures and Timing Skills

This section estimates hedge funds' pillar-level ESG sentiment exposures and timing skills using Equation (2). For each pillar $X \in \{E, S, G\}$, $\Delta\text{Sentiment}_t^X$ denotes the monthly change in pillar sentiment. Following Chen et al. (2021), β_{it}^{XSE} captures a fund's return sensitivity to changes in pillar-level sentiment.

$$Excess\ Return_{it} = \alpha_t + \beta_{it}^{XSE}\Delta Sentiment_t^X + \gamma_{it}^{XST;\,CCLL}MKT_{it}(\Delta Sentiment_t^X - \overline{\Delta Sentiment_{t-36}^X}) + \theta' f_t + \sum_{j=1}^{S_i-1}\rho_j StyleDummies_j + \sum_{q=1}^{Y_i-1}\eta_q YearDummies_{qi} + \varepsilon_t \quad (2)$$

Timing skill, $\gamma_{it}^{(XST;CCLL)}$, follows Cao et al. (2013) and measures how funds dynamically adjust exposures in response to detrended sentiment changes, defined as the deviation from the 36-month rolling mean. The detrending term $\Delta Sentiment_t^X - \overline{\Delta Sentiment_{t-36}^X}$ indicates whether the current sentiment change exceeds or falls below its 36-month rolling average. Larger β_{it}^{XSE} indicates greater pillar exposure, while larger $\gamma_{it}^{(XST;CCLL)}$ reflects a stronger timing ability.

All regressions control for nine hedge fund factors (f_t; Chen et al., 2025), fund style and year fixed effects, with standard errors clustered by style and year.

4.2 Pillar Exposures and Timing Skills Predicting Performance

This section examines whether pillar-level exposures and timing skills predict future performance using Equation (3).[9] Panel A of Table 4 reports results for alpha, Sharpe ratio, appraisal ratio, and Sortino ratio. The interaction term $\tau_X(\hat{\beta}_{it-1}^{XSE} \times \hat{\gamma}_{it-1}^{XST})$captures whether funds with both high exposure and strong timing skill outperform.

$$\begin{aligned} &Sortino\ Ratio_{it}\ or\ Appraisal\ Ratio_{it}\ or\ CLTZ\ HF9\ Alpha_{it}\ or\ Sharpe\ Ratio = \\ &\alpha_{it} + \textstyle\sum_{X\in\{E,S,G\}}[\tau_X\left(\hat{\beta}_{it-1}^{XSE} \times \hat{\gamma}_{it-1}^{XST}\right) + \delta_{XSE}\hat{\beta}_{it-1}^{XSE} + \delta_{XST}\hat{\gamma}_{it-1}^{XST}] + \\ &\delta_{Investor}\hat{\gamma}_{it-1}^{Investor} + \delta^C C_{t-1} + \textstyle\sum_{j=1}^{14}\rho_j StyleDummies_j + \\ &\textstyle\sum_{q=1}^{11}\eta_q YearDummies_{qi} + \sum_{f=1}^{1487}\varphi_f FirmDummies_{qi} + \varepsilon_{it} \end{aligned} \tag{3}$$

Panel A of Table 4 shows that funds with superior timing and exposure generate additional monthly alpha of approximately 2%, 3%, and 1% for the environmental, social, and governance pillars, respectively. These effects extend to risk-adjusted measures, indicating that effective pillar timing enhances both absolute and relative performance.

[9] C_{t-1} represents a vector of variables, including average and 36-month rolling standard deviation of returns, leveraged or not indicator, onshore and high-water mark indicators, logarithm of assets, and fund incentive fee in year $t-1$. Furthermore, for Stdev. prediction, the rolling standard deviation in month $t-1$ will not be included.

[Insert Table 4]

Performance gains are strongest for the environmental and social pillars. Social timing delivers larger short-term gains, reflecting rapid market reactions to *workplace sentiment*, *trust*, and *customer satisfaction*. Environmental timing produces more persistent performance, consistent with sustained public attention to environmental practices and regulation.

4.3 Pillar Exposures and Timing Skills Predicting Risks

Motivated by the improvement in Sortino ratios, this section studies whether pillar timing reduces risk using Equation (4). Total risk is measured by rolling volatility, while downside risk is captured by tail risk and expected shortfall.

$$Stdev._{it} \ or \ Tail\ risk_{95\%,it} \ or \ Expected\ shortfalls_{95\%,it} = \alpha_{it} + \sum_{X\in\{E,S,G\}}[\tau_X(\hat{\beta}_{it-1}^{XSE} \times \hat{\gamma}_{it-1}^{XST}) + \delta_{XSE}\hat{\beta}_{it-1}^{XSE} + \delta_{XST}\hat{\gamma}_{it-1}^{XST}] + \delta_{Investor}\hat{\gamma}_{it-1}^{Investor} + \delta^C C_{t-1} + \sum_{j=1}^{14}\rho_j StyleDummies_j + \sum_{q=1}^{11}\eta_q YearDummies_{qi} + \sum_{f=1}^{1487}\varphi_f FirmDummies_{qi} + \varepsilon_{it} \quad (4)$$

Panel B of Table 4 shows that environmental and social pillar timing significantly reduces both total and downside risk. Funds with stronger exposure and timing experience at least a 3% reduction in volatility and a 4% reduction in downside risk, highlighting the role of ESG sentiment timing in risk management.

4.4 Dissecting Downside Risk Mitigation Outcomes

To further examine downside risk management, this section applies the Henriksson–Merton (1981; HM) framework with daily sentiment adjustments from Goetzmann et al. (2000; GII). This approach distinguishes exposure increases during favorable sentiment from defensive adjustments during unfavorable periods.

$$Excess\ Return_{it} = \alpha_t + \beta_{it}^{XSE;HM\&GII}(\Delta Sentiment_t^X - \overline{\Delta Sentiment_{t-36}^X}) + \gamma_{it}^{XST;\,HM\&GII} - \ max(0, \Delta Sentiment_t^X - \overline{\Delta Sentiment_{t-36}^X}) + \theta' f_t + \sum_{j=1}^{S_i-1} \varphi_j StyleDummies_j + \sum_{q=1}^{Y_i-1} \eta_q YearDummies_{qi} + \varepsilon_t \quad (5)$$

Panel A of Table 5 presents 5×5 portfolio sorts by pillar exposure and timing skill. Alpha increases monotonically across quintiles, with the largest spreads in the environmental (16 bps) and social (25 bps) pillars. Panel B, using the Cao et al. (2013) method, suggests similar results.

[Insert Table 5]

Table 6 shows that over 36% of funds exhibit significant pillar exposures, and among these, more than 65% demonstrate significant timing skills, indicating that higher exposure is typically accompanied by superior timing.

[Insert Table 6]

4.5 Hedge Fund Timing Skills Across Strategies

This section examines how hedge funds' timing abilities vary across different strategies. Following Bali et al. (2014), funds are categorized as directional, semi-directional, and nondirectional based on their investment styles. Directional and semi-directional funds typically have higher market risk exposures, which may facilitate superior timing skills, whereas nondirectional funds are mostly market-neutral and less sensitive to market risks. Since pillar sentiment trajectories are measured at the market level,we analyze how timing skills differ across these strategy types. Panel B of Table 6 presents the percentage of significant pillar timing skills (row-wise) across strategies (column-wise).

The results indicate that directional and semi-directional funds exhibit a higher percentage of significant timing skills, particularly for environmental and social pillars. Panel C reports the mean exposures and timing skills, showing that directional and semi-directional funds generally have higher mean exposures and timing skills for environmental and social pillars.

5. Hedge Fund Timing Skill Mechanism

Beyond the outcomes documented in Section 5, understanding the mechanism behind hedge funds' pillar timing skills is crucial. Specifically, we examine how funds adjust their stock positions around sentiment-change events—i.e., whether their pillar timing decisions are proactive or reactive.

Figure 4 shows changes in long-only positions for stocks with high pillar sentiment around quarters with dramatic market-level sentiment shifts. Green solid, blue dashed, and red dotted lines represent environmental, social, and governance pillar stocks, respectively. The x-axis indicates quarters relative to when market-level sentiment exceeds its 36-month rolling average (x = 0), and the y-axis shows changes in long positions for stocks with above-average pillar sentiment, within a [-2, +2] quarter window.

[Insert Figure 4]

The results indicate that hedge funds increase long positions in high-ESG sentiment stocks one quarter before a dramatic rise in market-level sentiment. This pattern is consistent across all three pillars, showing that funds not only possess timing skills but also implement them proactively within their strategies. They build positions before sentiment peaks and reduce exposure before it fades.

A key premise for benefiting from proactive timing is the presence of a lag between sentiment changes and subsequent price drift. Figure 5 presents an event study of cumulative abnormal returns (CAR) for representative metrics—Accounting Sentiment (G), Airborne Emissions Improvement (E), and Customer Satisfaction (S)—over a [-5, +5] day window. These metrics have the highest fund exposures within their respective pillars (37%, 35%, and 28% for E, S, and G, respectively). Day 0 corresponds to the top 20% increases (red) and decreases (black) in metric sentiment. The results reveal a lag of 1 (G), 2 (S), and 3 (E) days between dramatic sentiment shifts and CAR drift, highlighting that funds profit from anticipating these delayed price reactions.

[Insert Figure 5]

6. Robustness

This section evaluates the robustness of hedge funds' ESG pillar timing skills by examining the persistence of performance benefits, variations across measurement approaches, implications for fund flows, and determinants of engagement in ESG sentiment trading. We first assess whether funds with higher prior timing skills deliver persistent performance. Figures 6A and 6B show predictions for 9-factor alpha and Sortino ratios using 1–12 months' lagged environmental (E, green solid line), social (S, blue double-dashed line), and governance (G, red dotted line) pillar sentiments, based on the CCLL method. Consistent with Section 4, the main benefits arise from the environmental and social pillars: social pillar timing skills generate increased performance for at least seven months, environmental pillar timing skills produce more sustained benefits for at least ten months, and governance pillar timing skills show relatively short-term improvements of about two months. These findings indicate that superior pillar timing skills not only enhance next-month performance but also contribute to persistent alpha and downside-risk-adjusted returns.

[Insert Figure 6]

Next, we examine whether variations in timing skills across different measurement methods and strategies remain robust. Table 7 reports the average pillar timing skills using the HM and GII methods, conditional on whether funds exhibit above- or below-average CCLL timing skills and across fund strategies. Hedge funds with high pillar timing skills, particularly those using directional or semi-directional strategies, maintain higher timing skills under both HM and GII approaches, which emphasize downside risk and daily sentiment trajectories.

[Insert Table 7]

We then investigate whether stronger pillar timing skills translate into increased future fund inflows. Table 8 presents predictions of monthly fund flows using lagged pillar timing skills, conditional on tercile rankings of previous-month performance (Equation 6). Results indicate that the largest inflow benefits occur for high-performing funds, but even mid- and low-performing funds experience positive flows, though the magnitudes decrease monotonically across terciles. Mid- and lower-performing funds continue to experience positive fund flow effects, highlighting the broader appeal of superior timing skills.

$$Flow_{it} = \alpha_{it} + \alpha_{it} + \sum_{X\in\{E,S,G\}}[\delta^{X}_{HTT} High\ Trank_{t-1} \times \hat{\gamma}^{XST}_{it-1} +$$

$$\delta^{X}_{MTT} Mid\ Trank_{t-1} \times \hat{\gamma}^{XST}_{it-1} + \delta^{X}_{LTT} Low\ Trank_{t-1} \times \hat{\gamma}^{XST}_{it-1} + \delta_{XST}\hat{\gamma}^{XST}_{it-1}]$$

$$+\delta_{Investor}\hat{\gamma}^{Investor}_{it-1} + \delta_{HT} High\ Trank_{t-1} + \delta_{MT} Mid\ Trank_{t-1} +$$

$$\delta_{LT} Low\ Trank_{t-1} + \delta_{M} MFee_{t-1} + CFlow'^{\delta_{CFlow}}_{t-1} + \sum_{j=1}^{14}\rho_j StyleDummies_j +$$

$$\sum_{q=1}^{11}\eta_q YearDummies_{qi} + \sum_{f=1}^{1487}\varphi_f FirmDummies_{qi} + \varepsilon_{it} \tag{6}$$

[Insert Table 8]

The determinants of hedge funds' engagement in ESG sentiment trading are examined using fund-level characteristics related to asset allocation, investment focus, strategy, and geographic orientation. Using LASSO regression (Equation 7),[10] next-month ESG sentiment beta is predicted from these characteristics. Results in Table 9 reveal distinct patterns across pillars: environmental timing skills are stronger for funds investing in resource-intensive sectors (e.g., *Softs*, *Base Metals*, *Biotechnology*, *Shipping*) or environmentally-focused geographies (e.g., *Western Europe*, *Russia*); social timing skills are higher for funds adopting stakeholder-focused approaches (e.g., *Shareholder Activist*) or investing in socially oriented sectors (e.g., *Health Care*); and governance timing skills are elevated for funds concentrating on fixed income-related corporate securities, bonds, or event-driven strategies (e.g., *Bankruptcy*) where management quality directly impacts valuations. These findings demonstrate that hedge funds' ESG pillar timing skills are systematically linked to their investment orientation and focus.

[Insert Table 9]

Finally, we compare our ESG sentiment and pillar indices to relevant benchmark indices. For each pillar, we select the most relevant topic attention indices from Bybee et al.

---

[10] We use the LASSO approach because the dataset contains 129 related variables, many of which are highly correlated within the same indicator group (e.g., *Global Focus: North America* vs. *Global Focus: North America Excluding USA*). LASSO is well-suited for this setting as it selects the most relevant features while addressing multicollinearity. Since LASSO does not directly accommodate fixed effects or clustered standard errors, we calculate the average ESG sentiment beta for each fund and the averages of variables across asset allocation, investment approach, investment focus, and geographic focus categories. We then regress the fund-level average ESG sentiment beta on these averaged characteristics.

(2024) [BKMX] and climate change sentiment indices from Engle et al. (2020) [EGLKS] and Ardia et al. (2023) [ABBI]. Figure 2 in the Appendix shows that peaks and troughs in these topic indices correspond to major movements in our pillar indices. Table 3 in the Appendix presents a pillar-wise 'horse race' comparing our significant pillar sentiment timing skills with the BKMX, EGLKS, and ABBI indices. Negative-topic-linked indices (e.g., Disasters, Diseases, Bankruptcy, Corrections/amplifications) correlate with lower future performance and inflows and higher future risks, whereas positive- or neutral-topic indices (e.g., Environment) show the opposite. Importantly, when controlling for these benchmark indices, our three-pillar sentiment timing skills remain significant predictors of outperformance, increased inflows, and lower total and downside risks at the 5% level.

In summary, hedge funds' ESG pillar timing skills are persistent, robust across methodologies, and economically meaningful. These skills drive sustained performance, mitigate downside risk, and attract positive fund flows, with their effectiveness shaped by investment focus, strategy, and sectoral or geographic orientation.

7. Conclusion

This paper shows that hedge funds can effectively time values-based, market-level ESG sentiment to enhance performance and risk management. Using high-frequency, firm-level ESG sentiment data aggregated into composite and pillar-level indices, we find that funds—particularly those pursuing directional or semi-directional strategies—display significant ESG exposures and proactive timing ability, especially along the environmental and social pillars. Strong ESG timing skill is associated with persistent alpha, improved downside-risk-adjusted returns, and greater fund inflows, including among mid- and lower-performing funds, indicating that investors value these capabilities. Mechanism tests suggest that hedge funds anticipate shifts in pillar-level sentiment by increasing long positions ahead of sentiment surges and exploiting delayed price responses to public ESG perceptions. Fund characteristics such as sector focus, geographic exposure, and investment approach systematically predict ESG timing ability, highlighting the role of specialized expertise and resources in extracting ESG-related signals. Overall, the study extends the literature on hedge fund skill, institutional ESG engagement, and sentiment-based asset pricing by identifying ESG pillar timing as a distinct, forward-looking source of alpha and risk mitigation.

References

Aragon, G. O., Jiang, Y., Joenväärä, J., & Tiu, C. I. (2024). Are hedge funds exploiting climate concerns? *Working Paper*.

Ardia, D., Bluteau, K., Boudt, K., & Inghelbrecht, K. (2023). Climate change concerns and the performance of green vs. brown stocks. *Management Science*, 69(12), 7607-7632.

Aggarwal, R., Briscoe-Tran, H., Erel, I., & Starks, L. T. (2024). Public sentiment decomposition and shareholder actions. *Working Paper*.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, 61(4), 1645-1680.

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, 21(2), 129-151.

Bali, T. G., Brown, S. J., & Caglayan, M. O. (2014). Macroeconomic risk and hedge fund returns. *Journal of Financial Economics*, 114(1), 1-19.

Brøgger, A., & Kronies, A. (2024). Skills and sentiment in sustainable investing. *Copenhagen Business School Working Paper*.

Bybee, L., Kelly, B., Manela, A., & Xiu, D. (2024). Business news and business cycles. *The Journal of Finance*, 79(5), 3105-3147.

Caglayan, M. O., Canayaz, M., Simin, T. T., & Zhao, L. (2025). Macro sentiment and hedge fund returns. *Working Paper*.

Caglayan, M. O., Celiker, U., & Tepe, M. (2024). Are All Short-Term Institutional Investors Informed?. Financial Analysts Journal, 80(1), 99-117.

Cao, C., Chen, Y., Goetzmann, W. N., & Liang, B. (2018a). Hedge funds and stock price formation. *Financial Analysts Journal*, 74(3), 54-68.

Cao, C., Chen, Y., Liang, B., & Lo, A. W. (2013). Can hedge funds time market liquidity? *Journal of Financial Economics*, 109(2), 493-516.

Cao, C., Liang, B., Lo, A. W., & Petrasek, L. (2018b). Hedge fund holdings and stock market efficiency. *The Review of Asset Pricing Studies*, 8(1), 77-116.

Ceccarelli, M., Evans, R. B., Glossner, S., Homanen, M., & Luu, E. (2024a). ESG skill of mutual fund managers.

Ceccarelli, M., Glossner, S., & Homanen, M. (2023). Catering through transparency: Voluntary ESG disclosure by asset managers and fund flows. In *Proceedings of the EUROFIDAI-ESSEC Paris December Finance Meeting*.

Ceccarelli, M., Ramelli, S., & Wagner, A. F. (2024b). Low carbon mutual funds. *Review of Finance*, 28(1), 45-74.

Chen, Y., Han, B., & Pan, J. (2021). Sentiment trading and hedge fund returns. *The Journal of Finance*, 76(4), 2001-2033.

Chen, Y., Li, S. Z., Tang, Y., & Zhou, G. (2025). Anomalies as New Hedge Fund Factors. *Journal of Financial and Quantitative Analysis, forthcoming.*

Chen, Y., & Liang, B. (2007). Do market timing hedge funds time the market? *Journal of Financial and Quantitative Analysis*, 42(4), 827-856.

Chen, Z., Lu, A., & Zhu, X. (2025). Investor sentiment and the pricing of macro risks for hedge funds. *Management Science*, 71(2), 1623-1645.

Cao, C., Chen, Y., Liang, B., & Lo, A. W. (2013). Can hedge funds time market liquidity? *Journal of Financial Economics*, 109(2), 493-516.

Cornell, B. (2021). ESG preferences, risk and return. *European Financial Management*, 27(1), 12 19.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging climate change news. *The Review of Financial Studies*, 33(3), 1184-1216.

Eskildsen, M., Ibert, M., Jensen, T. I., & Pedersen, L. H. (2024). In search of the true greenium. *Working Paper*.

Ferrell, A., Liang, H., & Renneboog, L. (2016). Socially responsible firms. *Journal of Financial Economics*, 122(3), 585-606.

Goetzmann, W. N., Ingersoll Jr, J., & Ivković, Z. (2000). Monthly measurement of daily timers. *Journal of Financial and Quantitative Analysis*, 35(3), 257-290.

Grinblatt, M., Jostova, G., Petrasek, L., & Philipov, A. (2020). Style and skill: Hedge funds, mutual funds, and momentum. *Management Science*, 66(12), 5505-5531.

Griffin, J. M., & Xu, J. (2009). How smart are the smart guys? A unique view from hedge fund stock holdings. *The Review of Financial Studies*, 22(7), 2531-2570.

Henriksson, R. D., & Merton, R. C. (1981). On market timing and investment performance. II. Statistical procedures for evaluating forecasting skills. *Journal of Business*, 513-533.

Ilhan, E., Krueger, P., Sautner, Z., & Starks, L. T. (2023). Climate risk disclosure and institutional investors. *The Review of Financial Studies*, 36(7), 2617-2650.

Kim, S., & Yoon, A. (2023). Analyzing active fund managers' commitment to ESG: evidence from the United Nations Principles for Responsible Investment. *Management science*, 69(2), 741-758.

Kuang, H., Liang, B., Qu, T., & Sherman, M. G. Are the Hedges of Funds Green? *Working Paper*.

Lachance, S., & Stroehle, J. C. (2021). The origins of ESG in pensions: strategies and outcomes. *Wharton Pension Research Council Working Paper*, 13.

Liang, H., Sun, L., & Teo, M. (2022). Responsible hedge funds. *Review of Finance*, 26(6), 1585-1633.

Liang, B., Pelizzon, L., Qu, T., & Getmansky Sherman, M. (2024). Sustainable Short Selling. *Working Paper*.

Pancholi, D. (2022). Hedge funds: resolving myths about ESG integration. *The Journal of Alternative Investments*.

Pástor, L., Stambaugh, R. F., & Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics*, 142(2), 550-571.

Pástor, L., Stambaugh, R. F., & Taylor, L. A. (2022). Dissecting green returns. *Journal of Financial Economics*, 146(2), 403-424.

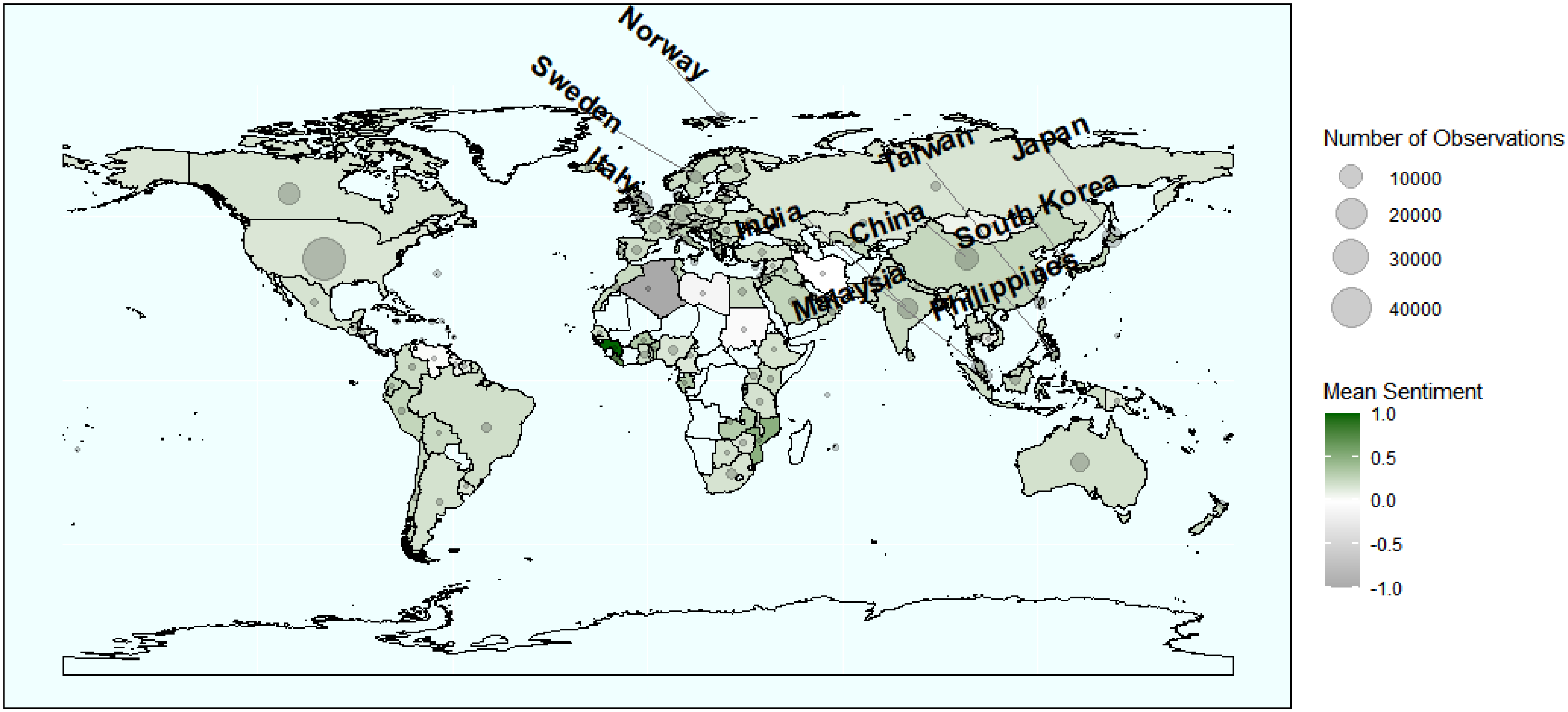
Pástor, L., Stambaugh, R. F., & Taylor, L. A. (2023). Green tilts. *NBER Working Paper*.

Serafeim, G. (2020). Public sentiment and the price of corporate sustainability. *Financial Analysts Journal*, 76(2), 26-46.

Figure 1 Country-level ESG Sentiment

This figure illustrates the average environmental (Figure 1A), social (Figure 1B), and governance (Figure 1C) sentiment across firms' domicile countries, as measured by LSEG MarketPsych ESG Analytics from January 2003 to December 2024.[14] Brighter colors indicate more positive sentiment, while grayer tones reflect more negative sentiment. Bubble size represents the total number of news observations for each ESG pillar. Bolded country names denote those ranking in the top 10 for average pillar sentiment and having total observations equal to or above the cross-country average for the respective pillar.

Figure 1A Environmental Pillar Sentiment



[14] The net sentiment variables range from -1 to 1, include 7 environmental, 11 social, and 5 governance variables.

Figure 1B Social Pillar Sentiment

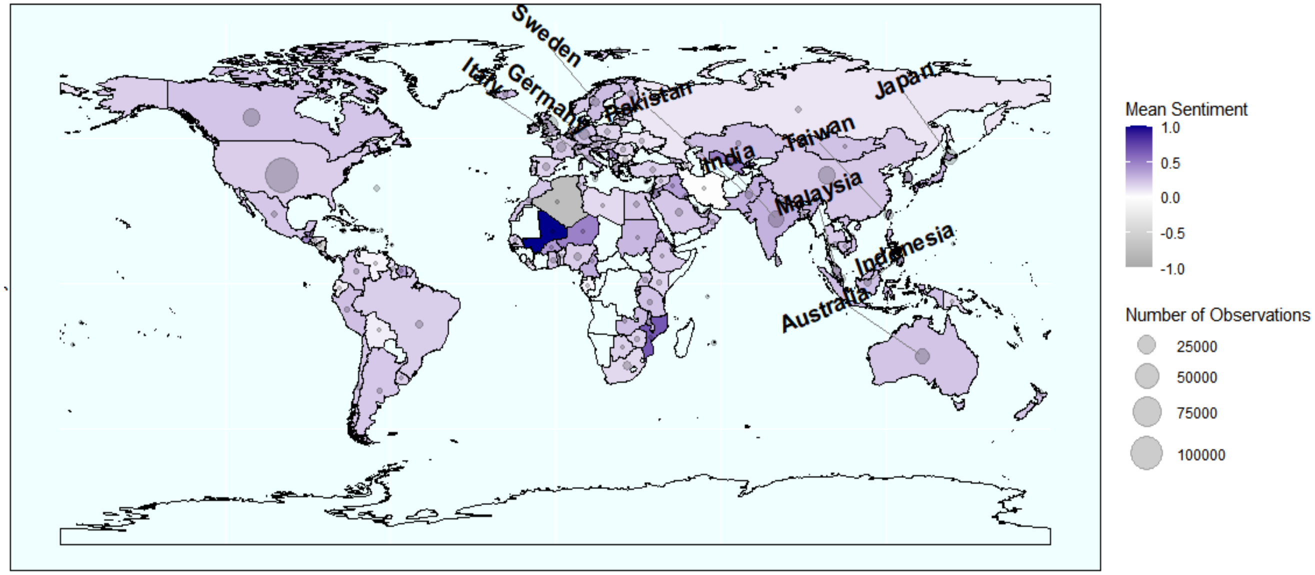


Figure 1C Governance Pillar Sentiment

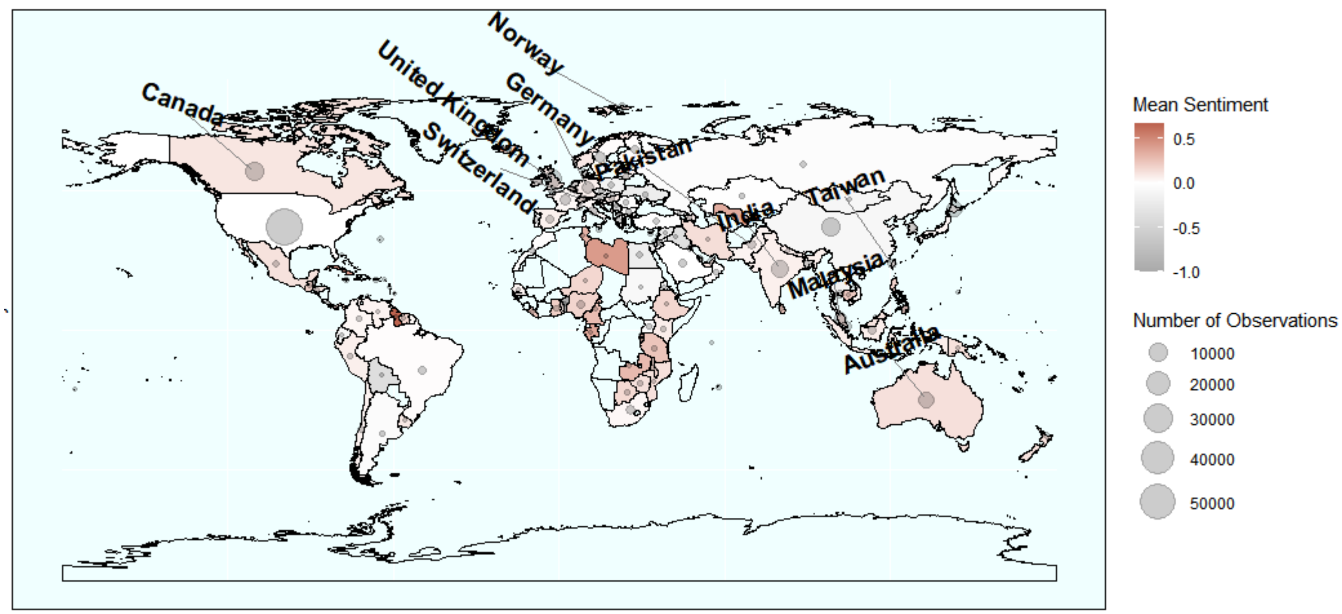
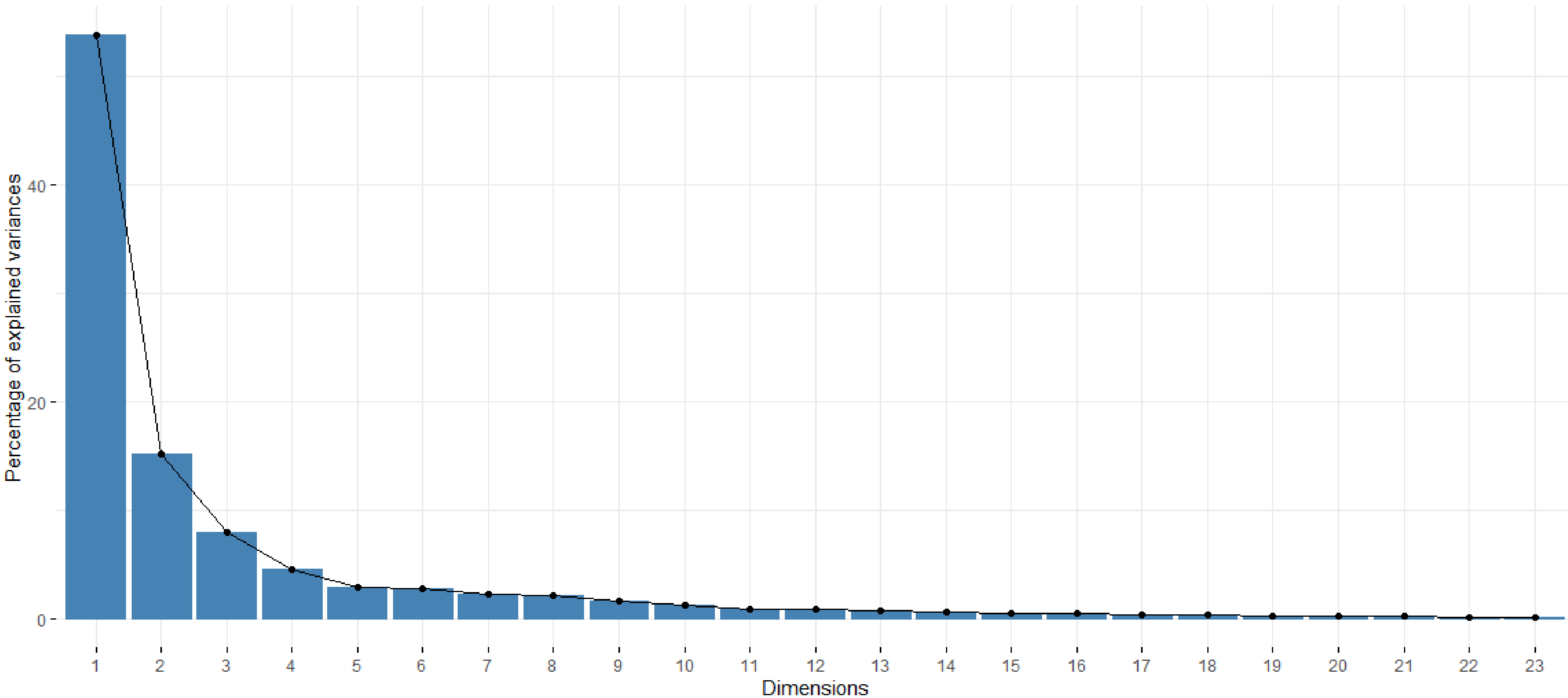


Figure 2 PCA Explained Variance Plot for ESG Sentiment Variables

This figure shows the explained variance of the 23 orthogonal dimensions derived from net sentiment variables within the environmental, social, and governance pillars, based on LSEG MarketPsych ESG Analytics data from January 2003 to December 2004.[15]

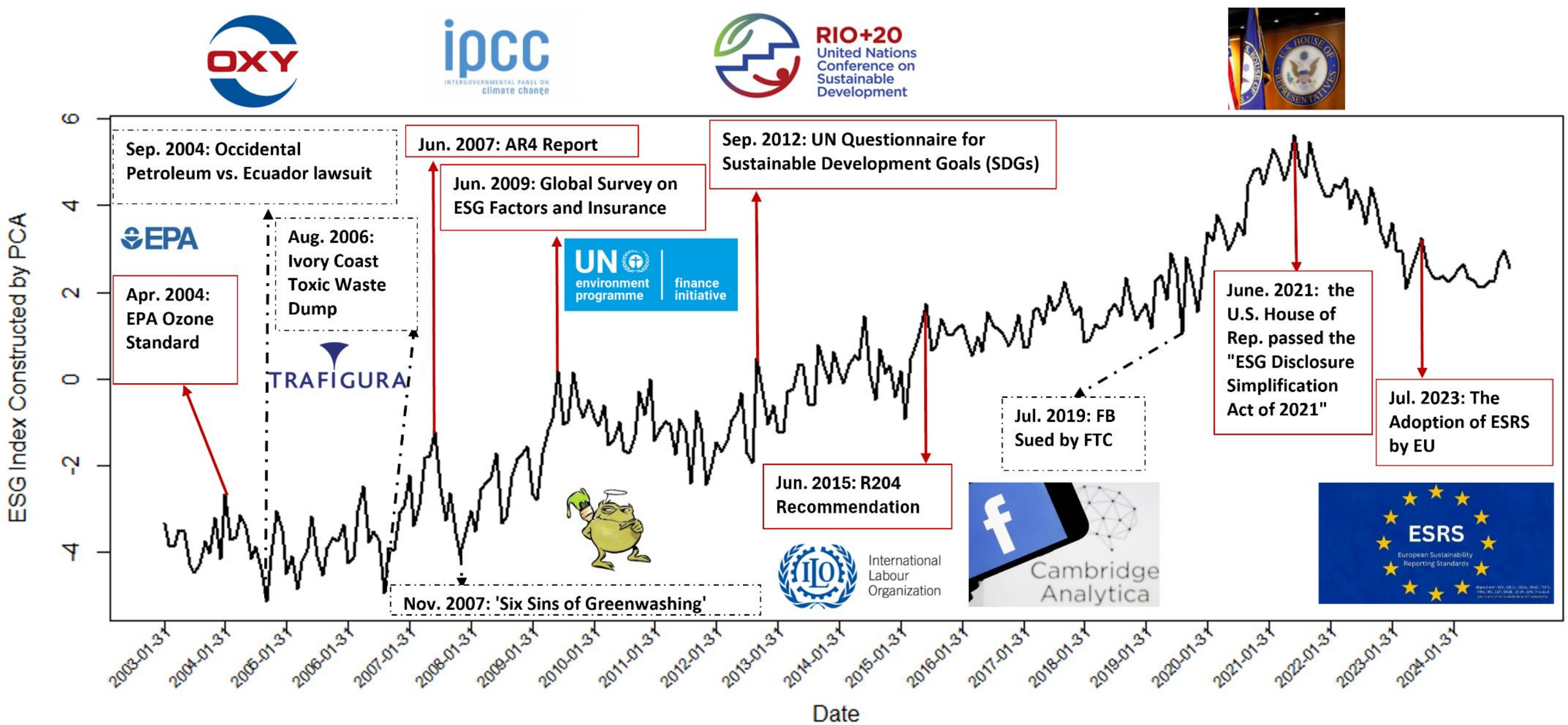


[15] The original net sentiment variables are on firm-level,we aggregate to the monthly level by taking the average of each variable within the respective month. The net sentiment variables range from -1 to 1, include 7 environmental, 11 social, and 5 governance variables.

Figure 3 PCA Constructed Composite and Pillar-wise ESG Sentiment Indices

This set of figures presents the composite (Figure 3A) and pillar-level (Figure 3B) ESG sentiment indices, constructed using Principal Component Analysis (PCA) on 23 net sentiment variables across the environmental, social, and governance pillars. The indices are based on LSEG MarketPsych ESG Analytics data and are shown for two periods: January 2003 to December 2004 at the monthly frequency.[16] The loadings of the first principal component are used as weights for the 23 variables (7 Environmental, 11 Social, and 5 Governance). For each pillar, only the relevant loadings are applied to calculate the corresponding index. The grey shaded area indicates the recession period as defined by the NBER.

Figure 3A Composite ESG Sentiment Index



---

[16] The original net sentiment variables are on firm-level,we aggregate to the monthly level by taking the average of each variable within the respective month. The net sentiment variables range from -1 to 1, include 7 environmental, 11 social, and 5 governance variables.

Figure 3B Pillar-wise ESG Sentiment Index

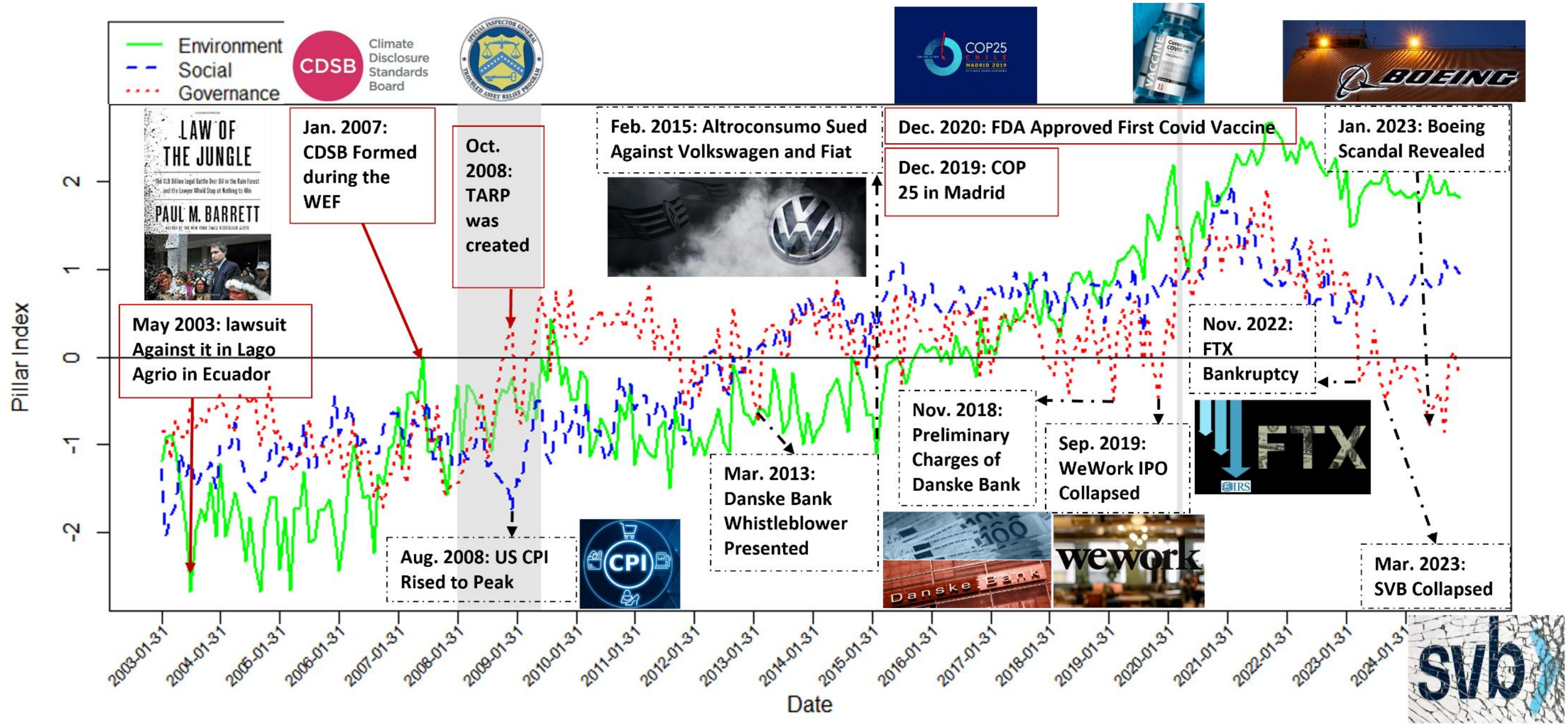


Figure 4 Hedge Fund Long-Only Share Changes Around Above-Average ESG and Pillar Sentiment Changes

This figure illustrates the quarterly changes (in %) in hedge funds' long positions for stocks with high ESG pillar sentiment. The x-axis represents quarters relative to periods of above-average ESG pillar sentiment changes. "0" denotes the quarter containing months with above-average monthly sentiment changes within a 36-month rolling window. –2, –1, 1, and 2 indicate two and one quarters before and after these periods, respectively. Each data point represents the average rate of change in long positions for funds holding stocks with above-average pillar sentiment during the corresponding quarters.

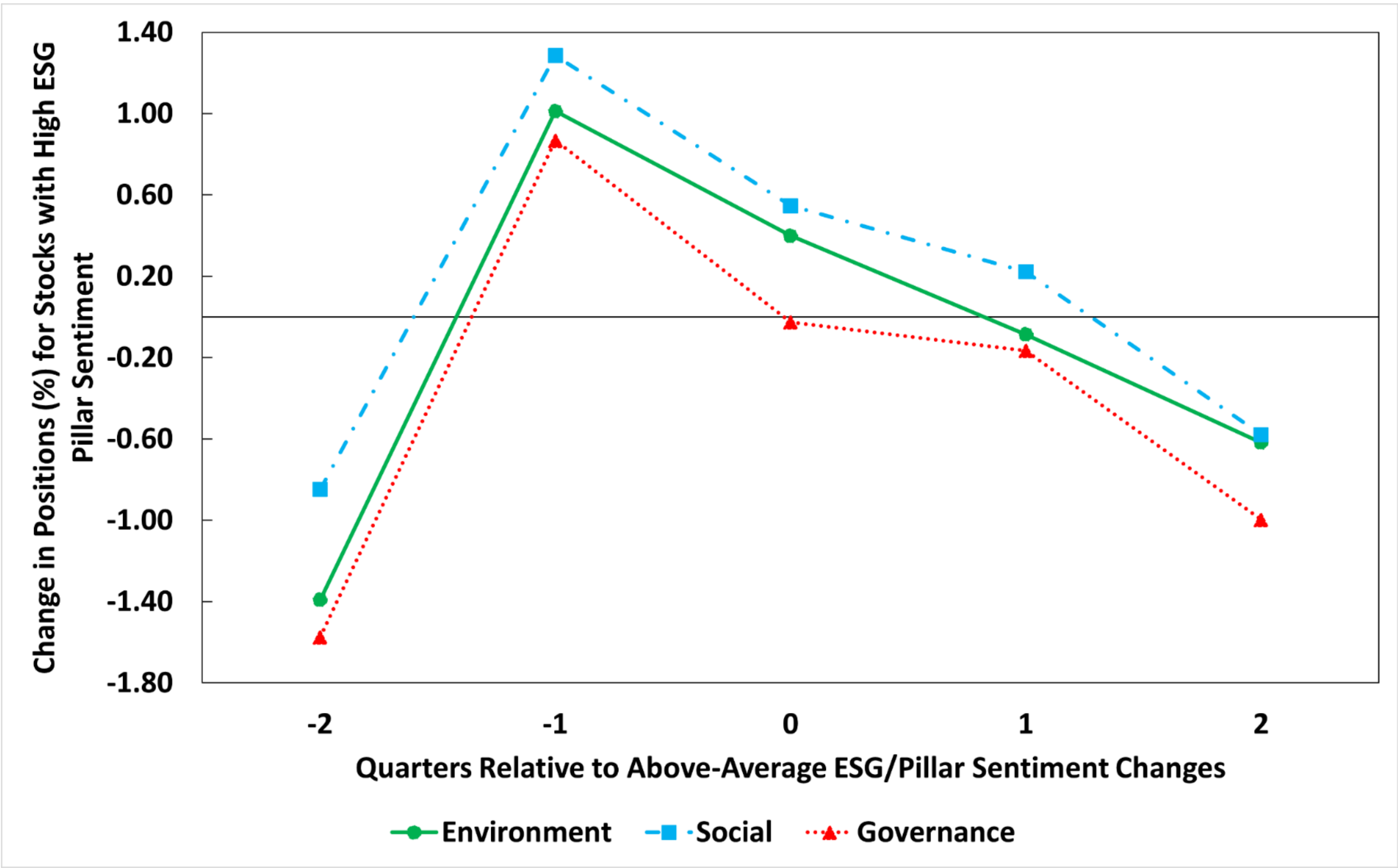


Figure 5 ESG Sentiment Changes Event Study

This set of figures presents an event study of ESG sentiment changes and their associated cumulative abnormal returns (CARs). The plots compare stocks experiencing the top 20% increases (red solid lines) and decreases (black double-dashed lines) in three sentiment metrics: accounting sentiment (G), airborne emissions improvement (E), and customer satisfaction (S). The x-axis denotes event days relative to the top 20% positive or negative sentiment changes, and the y-axis shows the CAR drift within a [-10, +10] day window. The orange-shaded areas highlight the 1–5 days following the sentiment change events. Confidence intervals are calculated at the 95% level.

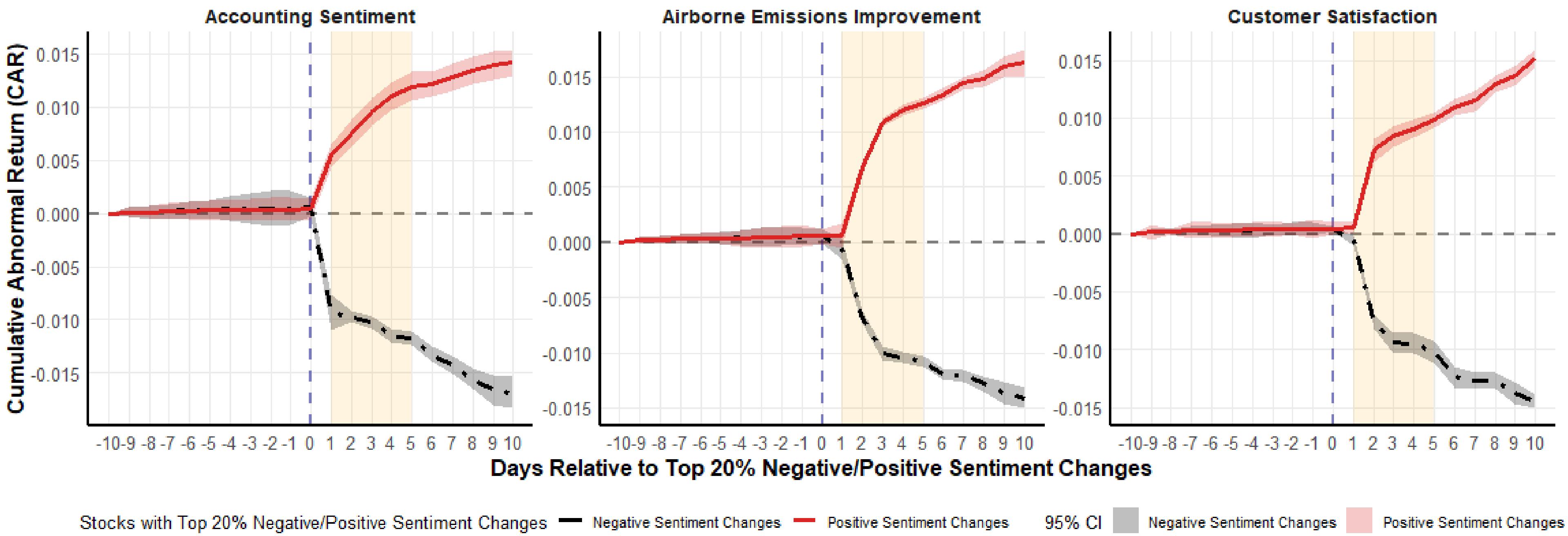


Figure 6 Persistence of ESG Sentiment Timing Skills in Predicting Alphas and Sortino Ratios

This set of figures examines whether hedge funds' pillar-level timing skills, lagged by 1 to 12 months, predict future performance. Figure 6A presents results for the 9-factor alpha, and Figure 6B for the Sortino ratio.[17] The points indicate the estimated coefficients of the lagged timing skills, and the stars denote statistical significance levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 6A Persistence of ESG Sentiment Timing Skills in Predicting Alphas

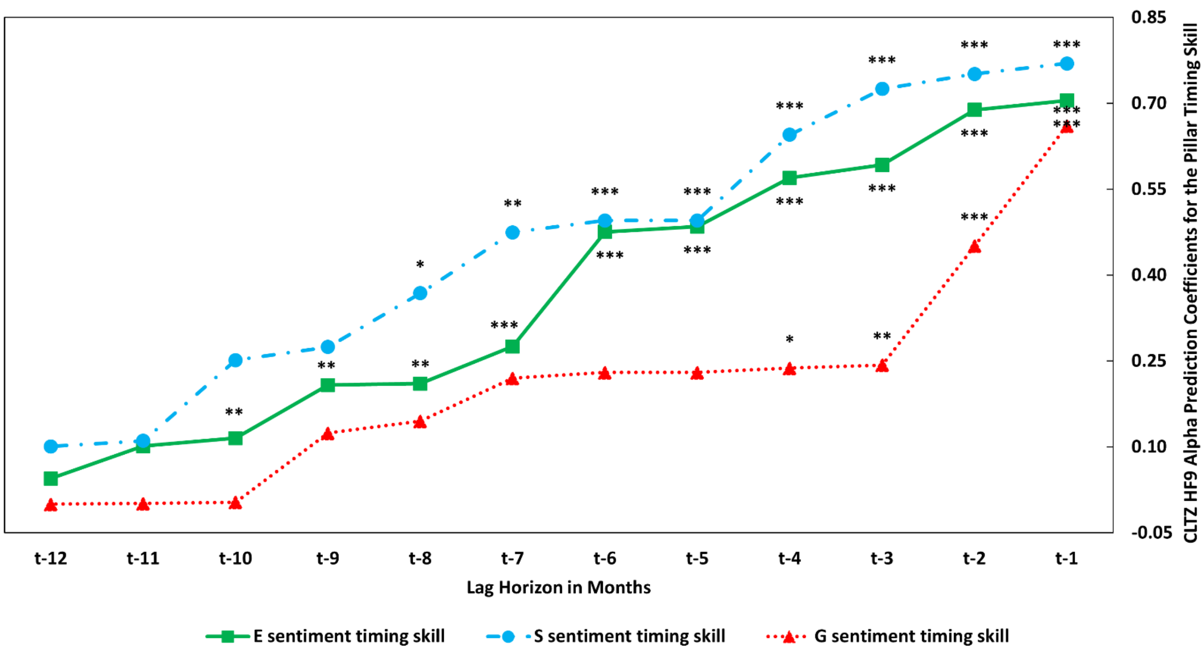
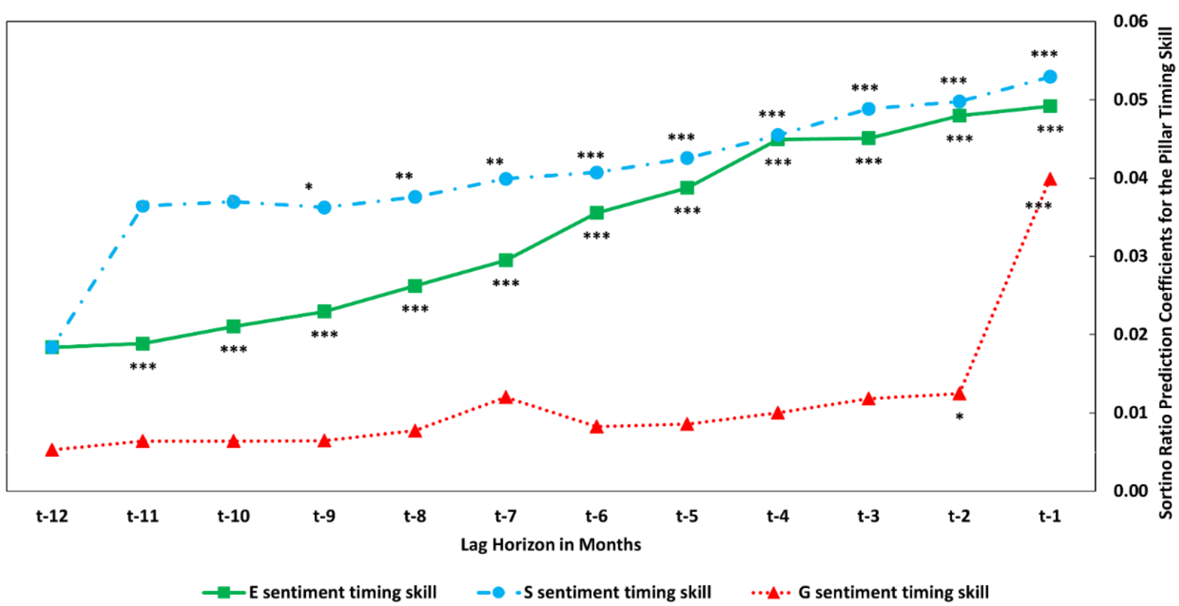


Figure 6B Persistence of ESG Sentiment Timing Skills in Predicting Sortino Ratios



[17] The CLTZ HF9 alpha for each fund is calculated by $Excess\ Return_t = \alpha_t + \theta' f_t + \varepsilon_t$. $Excess\ Return_t$ is calculated by using a fund's monthly return minus the 3-month US Treasury Bill return at month t. Sortino ratio is calculated by $\frac{Excess\ Return}{Stdev.(R_{ret<Tar})}$ in a rolling 36-month window.

Table 1 Descriptive Statistics of TASS, ESG Sentiment Variables & Indices, and Hedge Fund ESG Sentiment Beta

This table reports the number of observations, minimum, mean, maximum, and standard deviation for the public sustainable sentiment variables, as well as the composite and pillar indices monthly (Panel A), and fund-level TASS performance, risks, fees, characteristics, and the 36-month rolling ESG and pillar sentiment betas (Panel B). The net sentiment variables, ranging from -1 to 1, include 7 environmental, 11 social, and 5 governance variables, based on LSEG MarketPsych ESG Analytics data from January 2012 to December 2024.[18] The observations in Panel B are presented at the fund level.[19] The pillar sentiment exposures and timing skills are estimated based on a 36-month rolling window. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

[18] This is to align with the time range of the sentiment variables and TASS data.

[19] All non-US domiciled funds' assets under management are converted to US dollars using the annual exchange rates provided by the OECD (https://data.oecd.org/conversion/exchange-rates.htm). A total of 9,343 funds (1,074 companies) is excluded due to reporting quarterly or gross-of-fee returns or having assets under management (AUM) of less than $10 million. Additionally, 3,727 funds (756 companies) are excluded for having fewer than 36 months of monthly return data. 338 funds lack ESG and pillar sentiment betas due to non-convergence of t-statistics during the beta estimation regression.

The CLTZ HF9 alpha for each fund is calculated by $Excess\ Return_t = \alpha_t + \theta' f_t + \varepsilon_t$. $Excess\ Return_t$ is calculated by using a fund's monthly return minus the 3-month US Treasury Bill return at month t. $Stdev.$ is the rolling 36-month standard deviations. Sortino ratio is calculated by $\frac{Excess\ Return}{Stdev.(R_{ret<Tar})}$ in a rolling 36-month window. $Stdev.(R_{ret<Tar})$ is the standard deviation of the monthly returns that are smaller than the 3-month US Treasury Bill returns in the related months.

The rolling appraisal ratio is calculated by regressing the 36 months excess returns of fund i on the excess return of the fund's TASS-style index j within the same year (BGLS, 2008). Specifically, $r_{it} - R_{ft} = \alpha_{it} + \beta_i(r_{jt} - R_{ft}) + \varepsilon_{it}$, where R_{ft} is the 3-month US Treasury Bill return. The appraisal ratio is calculated as α_{it} divided by standard deviation of the residuals (ε_{it}).

Fund flow is calculated by $Flow_{i,t} = \frac{Assets_{i,t} - Assets_{i,t-1} * (1 + Return_{i,t})}{Assets_{i,t-1}}$.

According to Liang and Park (2010), the 95% expected shortfall is calculated by $ES_t(95\%, \tau) = -E_t[R_{t+\tau} | R_{t+\tau} \leq -VaR_t(95\%, \tau)]$, and the tail risks is calculated by $Tail\ risk_{95\%} = \sqrt{E_t[(R_{t+\tau} - E_t(R_{t+\tau}))^2 | R_{t+\tau} \leq -VaR_t(95\%, \tau)]}$. $R_{t+\tau}$ is the portfolio return during the period from t to $t + \tau$. Both are calculated using a rolling 36-month window.

	Panel A: Public Sustainable Sentiment Variables						
		N	Min	Mean	Median	Max	Stdev.
E Pillar	Airborne Emissions Improvement	264	-0.33	0.03	0.02	0.27	0.14
	Carbon Emissions Improvement	264	-0.02	0.20	0.22	0.30	0.06
	Pollution Improvement	264	-0.36	-0.15	-0.16	0.00	0.08
	Sustainability Improvement	264	-0.15	0.10	0.07	0.33	0.12
	Energy Efficiency Efforts	264	0.10	0.24	0.23	0.33	0.04
	Supply Chain Sustainability	264	-0.06	0.18	0.19	0.30	0.06
	Climate Policy	264	0.01	0.23	0.23	0.49	0.07
S Pillar	Access Affordability	264	0.35	0.45	0.43	0.55	0.05
	Public Health Support	264	-0.34	-0.05	-0.05	0.21	0.07
	Trust	264	0.03	0.15	0.15	0.29	0.06
	Customer Satisfaction	264	-0.06	0.09	0.10	0.17	0.05
	Privacy Efforts	264	-0.13	0.06	0.07	0.24	0.06
	Product Sentiment	264	-0.05	0.11	0.11	0.28	0.05
	Diversity Efforts	264	0.00	0.13	0.13	0.26	0.05
	Wage Fairness	264	-0.19	-0.13	-0.13	-0.06	0.03
	Workplace Development	264	0.20	0.27	0.27	0.36	0.02
	Workplace Safety Efforts	264	-0.11	-0.02	-0.02	0.14	0.04
	Workplace Sentiment	264	-0.17	-0.01	-0.01	0.13	0.07
G Pillar	Management Diversity	264	0.27	0.38	0.38	0.53	0.04
	Management Sentiment	264	-0.11	-0.04	-0.04	0.05	0.03
	Management Trust	264	-0.14	-0.03	-0.03	0.05	0.03
	Shareholders	264	-0.50	-0.19	-0.17	0.19	0.15
	Accounting Sentiment	264	-0.40	-0.17	-0.15	0.03	0.09
Sentiment Index	ESG Sentiment Index	264	-5.12	0.00	0.18	5.63	2.72
	Environmental Sentiment Index	264	-2.68	0.00	-0.29	2.67	1.36
	Social Sentiment Index	264	-2.04	0.00	0.34	1.97	0.91
	Governance Sentiment Index	264	-1.72	0.00	0.07	1.92	0.75

Panel B: TASS Variables, ESG Pillar Sentiment Exposures, and Timing Skills							
		N	Min	Mean	Median	Max	Stdev.
Performance and Risks	Return	4,557	-5.49	0.45	0.49	5.21	0.62
	Stdev. (36m)	4,541	0.08	2.22	1.54	124.04	3.37
	Skewness	4,554	-8.45	-0.32	-0.21	9.31	1.09
	Kurtosis	4,554	-1.97	2.36	0.41	119.66	6.36
	Sortino Ratio (36m)	4,532	-3.47	0.00	0.06	3.67	0.79
	CLTZ HF9 Alpha (36m)	4,543	-0.95	0.06	0.03	0.78	0.46
	Appraisal ratio (36m)	956	-4.48	0.09	0.03	4.58	0.58
	Tail risk (95%)	4,541	0.09	4.23	3.03	61.21	4.00
	Expected Shortfall (95%)	4,541	-46.57	-3.56	-2.56	0.89	3.77
Fees	Management Fee	4,150	0.00	1.37	1.50	6.00	0.72
	Incentive Fee	2,362	0.03	17.09	20.00	50.00	5.50
Characteristics	Min. Investment ($M)	4,476	0.00	3.47	0.10	5,000.00	81.38
	Assets ($M)	4,557	10.00	163.07	49.23	32,531.51	631.28
	Age	4,557	1.49	10.75	9.85	39.20	5.51
	Leveraged	4,557	0.00	0.44	0.30	1.00	0.46
	Margin	2,884	0.00	0.19	0.00	1.00	0.39
	High Water Mark	4,529	0.00	0.38	0.00	1.00	0.48
	Lock up Period	4,557	0.00	1.73	0.00	84.00	5.48
	Sub. Freq.	4,557	0.00	12.45	21.00	252.00	15.54
	Red. Freq.	4,557	0.00	23.59	21.00	252.00	39.27
	Onshore	4,557	0.00	0.14	0.00	1.00	0.35
ESG Pillar Sentiment Exposures and Timing Skills	$\hat{\beta}^{EST}$	4,219	-45.46	0.12	0.12	15.76	2.14
	$\hat{\beta}^{SST}$	4,219	-28.86	0.15	0.18	31.93	4.00
	$\hat{\beta}^{GST}$	4,219	-9.84	0.11	0.11	35.11	1.90
	$\hat{\gamma}^{EST}$	4,219	-52.64	0.24	0.26	20.00	2.59
	$\hat{\gamma}^{SST}$	4,219	-31.39	0.25	0.26	22.00	2.33
	$\hat{\gamma}^{GST}$	4,219	-18.02	0.08	0.02	10.00	2.67

Table 2 Hedge Fund Excess Returns and Individual ESG Sentiment Variables

This table presents fund-level excess return exposures to the 23 monthly net sentiment indices (ranging from -1 to 1) provided by LSEG MarketPsych ESG Analytics, covering the period from January 2012 to December 2024.[20] The coefficients in Panel A are estimated using the equation below.

$$Excess\ Return_t = \alpha_t + \beta^{Indp}\Delta Sentiment_{tp}^{Ind} + \theta' f_t + \sum_{j=1}^{S_i-1} \rho_j StyleDummies_j + \sum_{q=1}^{Y_i-1} \eta_q YearDummies_{qi} + \varepsilon_t$$

The excess return[21] is regressed on the changes in sentiment variable p ($\Delta Sentiment_{tp}^{Ind}$) for each fund i at month t. $\Delta Sentiment_{tp}^{Ind}$ is calculated as $Sentiment_{tp}^{Ind} - Sentiment_{t-1\,p}^{Ind}$. f_t represents the nine hedge fund factors selected by Chen et al. (2025), which include the equity market, asset growth, betting against beta, low-risk, return-on-assets, time-series momentum, monthly changes in the 10-year Treasury yield, monthly changes in credit yield spread, and term spread factors.[22] Y_i and S_i represent the total number of years and styles for fund i. Panel A presents the average of β^{Ind} and adjusted R^2 for sentiment variable p across all funds, along with the descending order ranks based on the average β^{Ind} values. TASS style and year dummies are included in the regression, along with clustered standard errors for both style and year. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Panel B presents summary statistics (total number, median, and sum rank) for the variables in environmental, social, and governance pillar according to Panel A. Panel C provides the Kruskal-Wallis Test comparing the relative importance of the three pillars.[23]

[20] This is to align with the time range of the sentiment variables and TASS data.

[21] $Excess\ Return_t$ is calculated by using a fund's monthly return minus the 3-month US Treasury Bill return at month t.

[22] We get the data from Yong Chen's website: https://sites.google.com/site/yongchenfinance/.

[23] The H Statistic is calculated by $H = [\frac{12}{n(n+1)}\sum_{j=1}^{c}\frac{T_j^2}{n_j}] - 3(n+1)$. Where n is the total sample size for all groups, c is the number of the groups (in our case, it equals to 2), T_j is the sum of the ranks in the jth group, and n_j is the size of the jth group

Panel A: Average Coefficients and Adjusted R^2 for the Individual ESG Sentiment Betas					
Variable	Pillar	Coef.		Rank	Adj. R^2
Customer Satisfaction	Social	0.37	**	1	67.98%
Airborne Emissions Improvement	Environment	0.35	**	2	69.18%
Workplace Sentiment	Social	0.32	**	3	66.39%
Trust	Social	0.28	**	4	64.53%
Accounting Sentiment	Governance	0.28	**	5	68.24%
Privacy Efforts	Social	0.26	**	6	65.61%
Sustainability Improvement	Environment	0.26	**	7	65.87%
Energy Efficiency Efforts	Environment	0.24	**	8	63.49%
Climate Policy	Environment	0.22	**	9	63.30%
Pollution Improvement	Environment	0.12	**	10	66.81%
Public Health Support	Social	0.06	**	11	61.91%
Access Affordability	Social	0.06	**	12	65.15%
Product Sentiment	Social	0.05	**	13	71.96%
Shareholders	Governance	0.05	**	14	67.01%
Workplace Safety Efforts	Social	0.04	**	15	66.64%
Wage Fairness	Social	0.03	**	16	63.91%
Management Sentiment	Governance	0.02	**	17	65.07%
Supply Chain Sustainability	Environment	0.01	**	18	64.94%
Carbon Emissions Improvement	Environment	0.01	**	19	66.13%
Diversity Efforts	Social	-0.07	**	20	63.95%
Management Diversity	Governance	-0.12	**	21	66.11%
Management Trust	Governance	-0.14	**	22	66.88%
Workplace Development	Social	-0.15	**	23	63.45%

Table 2 Continued

Panel B: The Median & Sum of the Coefficient Rank and the Number of Variables in Each Pillar			
	Median Rank	Num. of Var.	Sum Rank
Environment	9.00	7.00	73.00
Social	12.00	11.00	124.00
Governance	17.00	5.00	79.00

Panel C: Kruskal-Wallis Test for the Coefficient Rank — Relative Importance of the Pillars			
	Environment vs. Social	Environment vs. Governance	Social vs. Governance
H	24,488.60	22,219.92	29,833.44
Decision	**Reject**	**Reject**	**Reject**

Table 3 PCA Constructed ESG Sentiment Loadings and Pillar Relative Importance

This table reports the first principal component loadings from PCA on 23 monthly ESG sentiment variables (January 2012–December 2024). Panel A ranks loadings by magnitude. Panel B summarizes the number, median, and total rank of variables within the environmental, social, and governance pillars. Panel C presents Kruskal–Wallis tests comparing the relative importance of the three pillars.[24]

Panel A: First Principal Component Variable Loadings			
ESG Sentiment Variables	Pillar	Loadings	Rank
Shareholders	Governance	0.48	1
Airborne Emissions Improvement	Environment	0.45	2
Sustainability Improvement	Environment	0.45	3
Pollution Improvement	Environment	0.25	4
Accounting Sentiment	Governance	0.22	5
Carbon Emissions Improvement	Environment	0.17	6
Workplace Sentiment	Social	0.17	7
Trust	Social	0.17	8
Access Affordability	Social	0.17	9
Supply Chain Sustainability	Environment	0.15	10
Climate Policy	Environment	0.14	11
Customer Satisfaction	Social	0.13	12
Product Sentiment	Social	0.13	13
Workplace Safety Efforts	Social	0.13	14
Diversity Efforts	Social	0.13	15
Management Sentiment	Governance	0.10	16
Privacy Efforts	Social	0.08	17
Public Health Support	Social	0.06	18
Energy Efficiency Efforts	Environment	0.06	19
Management Trust	Governance	0.04	20
Management Diversity	Governance	0.04	21
Wage Fairness	Social	0.03	22
Workplace Development	Social	0.01	23

Panel B: The Median of the 1st Principal Component (PC) Loadings Rank and the Number of Variables in Each Pillar			
	Median Rank	Num. of Var.	Sum Rank
Environment	6.00	7.00	55.00
Social	14.00	11.00	158.00
Governance	16.00	5.00	16.00
Panel C: Kruskal-Wallis Test for the 1st Principal Component Loadings Rank — Relative Importance of the Pillars			
	Environment vs. Social	Environment vs. Governance	Social vs. Governance
H	30,655.90	13,540.67	34,545.76
Decision	**Reject**	**Reject**	**Reject**

[24] The H Statistic is calculated by $H = [\frac{12}{n(n+1)}\sum_{j=1}^{c}\frac{T_j^2}{n_j}] - 3(n+1)$. Where n is the total sample size for all groups, c is the number of the groups (in our case, it equals to 2), T_j is the sum of the ranks in the jth group, and n_j is the size of the jth group

Table 4 ESG Sentiment Exposures and Timing Skills Predicting Performance and Risks

This table presents the performance (Panel A) and risk (Panel B) predictions using funds' 36-month rolling pillar sentiment exposures and skills.[25] The predictions are based on the model presented below.[26]

$$Sortino\ Ratio_{it}\ or\ Appraisal\ Ratio_{it}\ or\ CLTZ\ HF9\ Alpha_{it}\ or\ \ Sharpe\ ratio\ or\ Stdev._{it}\ \ or$$

$$Tail\ risk_{95\%,it}\ or\ Expected\ shortfalls_{95\%,it} = \alpha_{it} + \sum_{X\in\{E,S,G\}}[\tau_X\left(\hat{\beta}^{XSE}_{it-1} \times \hat{\gamma}^{XST}_{it-1}\right) + \delta_{XSE}\hat{\beta}^{XSE}_{it-1} + \delta_{XST}\hat{\gamma}^{XST}_{it-1}] +$$

$$\delta_{Investor}\hat{\gamma}^{Investor}_{it-1} + \delta^C C_{t-1} + \sum_{j=1}^{14}\rho_j StyleDummies_j + \sum_{q=1}^{11}\eta_q YearDummies_{qi} + \sum_{f=1}^{1487}\varphi_f FirmDummies_{qi} + \varepsilon_{it}$$

X denotes the ESG pillars (Environment, Social, or Governance). $\hat{\beta}^{XSE}_{it-1}$ is the estimated pillar exposures and $\hat{\gamma}^{XST}_{it-1}$ is the estimated pillar timing skills (CCLL) for fund i in month $t-1$. $\hat{\gamma}^{Investor}_{it-1}$ is the investor sentiment timing skill, measured by the sensitivity of fund i's excess return to detrended pillar sentiment changes, condition on the market equity factor (Cao et al., 2013).[27] The pillar exposures sentiment timing skills (Cao et al., 2013 [CCLL]) is estimated using the following equations:

$$Excess\ Return_{it} = \alpha_t + \beta^{XSE}_{it}\Delta Sentiment^X_t + \gamma^{XST;\,CCLL}_{it} MKT_{it}(\Delta Sentiment^X_t - \overline{\Delta Sentiment^X_{t-36}}) + \theta' f_t + \sum_{j=1}^{S_i-1}\rho_j StyleDummies_j + \sum_{q=1}^{Y_i-1}\eta_q YearDummies_{qi} + \varepsilon_t$$

f_t represents the nine hedge fund factors selected by Chen et al. (2025).[28] Y_i and S_i represent the total number of years and styles for fund i. All models in this table use TASS style, year, and firm dummies, along with clustered standard errors for style, year, and fund-firm pairs. The lower order terms ($\hat{\beta}^{XSE}_{it-1}$and $\hat{\gamma}^{XST}_{it-1}$) are controlled within all models. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

[25] The CLTZ HF9 alpha for each fund is calculated by $Excess\ Return_t = \alpha_t + \theta' f_t + \varepsilon_t$. $Excess\ Return_t$ is calculated by using a fund's monthly return minus the 3-month US Treasury Bill return at month t. $Stdev.$ is the rolling 36-month standard deviations. Sortino ratio is calculated by $\frac{Excess\ Return}{Stdev.(R_{ret<Tar})}$ in a rolling 36-month window. $Stdev.(R_{ret<Tar})$ is the standard deviation of the monthly returns that are smaller than the 3-month US Treasury Bill returns in the related months.
The rolling appraisal ratio is calculated by regressing the 36 months excess returns of fund i on the excess return of the fund's TASS-style index j within the same year (BGLS, 2008). Specifically, $r_{it} - R_{ft} = \alpha_{it} + \beta_i(r_{jt} - R_{ft}) + \varepsilon_{it}$, where R_{ft} is the 3-month US Treasury Bill return. The appraisal ratio is calculated as α_{it} devided by standard deviation of the residuals (ε_{it}). According to Liang and Park (2010), the 95% expected shortfall is calculated by $ES_t(95\%,\tau) = -E_t[R_{t+\tau}|R_{t+\tau} \le -VaR_t(95\%,\tau)]$, and the tail risks is calculated by $Tail\ risk_{95\%} = \sqrt{E_t[(R_{t+\tau} - E_t(R_{t+\tau}))^2|R_{t+\tau} \le -VaR_t(95\%,\tau)]}$. $R_{t+\tau}$ is the portfolio return during the period from t to $t+\tau$. Both are calculated using a rolling 36-month window.
[26] C_{t-1} represents a vector of variables, including average and 36-month rolling standard deviation of returns, leveraged or not indicator, onshore and high-water mark indicators, logarithm of assets, and fund incentive fee in year $t-1$. Furthermore, for Stdev. prediction, the rolling standard deviation in month $t-1$ will not be included.
[27] Specifically, the investor sentiment timing skill is captured by $\hat{\gamma}^{Investor}$, as defined in the equation below:

$$Excess\ Return_{it} = \alpha_t + \beta^{Investor}_{it}(\Delta Investor\ sentiment_t - \overline{\Delta Investor\ sentiment_{t-36}}) + \gamma^{Investor}_{it} MKT_{it}(\Delta Investor\ sentiment_t - \overline{\Delta Investor\ sentiment_{t-36}}) + \theta' f_t + \sum_{j=1}^{S_i-1}\varphi_j StyleDummies_j + \sum_{q=1}^{Y_i-1}\eta_q YearDummies_{qi} + \varepsilon_t$$

The $\Delta Investor\ sentiment_t$ represents changes in the orthogonalized investor sentiment index developed by Baker and Wurgler (2006), with data obtained from Jeffrey Wurgler's website (https://pages.stern.nyu.edu/~jwurgler/).
[28]We get the data from Yong Chen's website: https://sites.google.com/site/yongchenfinance/.

Panel A: Performance												
	Model 1			Model 2			Model 3			Model 4		
	CLTZ HF9 Alpha			Sharpe Ratio			Appraisal Ratio			Sortino Ratio		
	Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value	
$\hat{\gamma}^{EST} \times \hat{\beta}^{ESE}$	0.02	3.50	***	0.03	4.91	***	0.04	6.24	***	0.04	6.53	***
$\hat{\gamma}^{SST} \times \hat{\beta}^{SSE}$	0.03	3.15	***	0.04	3.53	***	0.05	4.38	***	0.05	4.90	***
$\hat{\gamma}^{GST} \times \hat{\beta}^{GSE}$	0.01	2.12	**	0.02	2.84	***	0.02	3.66	***	0.02	3.35	***
$\hat{\gamma}^{Investor}$	0.03	3.92	***	0.04	4.73	***	0.04	6.28	***	0.05	6.88	***
Return	0.17	6.31	***	0.11	5.83	***	0.11	5.97	***	0.16	7.80	***
Stdev.	-0.06	-7.64	***	-0.06	-2.69	***	-0.06	-7.67	***	-0.02	-4.63	***
Incentive fee	0.03	2.40	**	0.01	1.69	*	0.01	5.72	***	0.02	7.90	***
High water mark	0.08	2.72	***	0.08	2.45	**	0.06	2.29	**	0.05	6.21	***
Onshore	0.02	4.56	**	0.01	2.22	**	0.05	2.28	**	0.02	5.58	***
Leveraged	0.05	6.88	***	0.06	6.71	***	0.08	3.11	***	0.07	6.01	***
Log(Assets)	0.04	5.54	***	0.08	5.52	***	0.05	6.43	***	0.05	7.69	***
Controlled lower-order terms	Y			Y			Y			Y		
Style	Y			Y			Y			Y		
Fund–Firm	Y			Y			Y			Y		
Year	Y			Y			Y			Y		
Num. of Obs.	188,448			118,527			67,325			176,459		
Adj. R^2	3.26%			3.44%			6.85%			6.96%		

Panel B: Risks									
	Model 1			Model 2			Model 3		
	Stdev.			Expected Shortall (95%)			Tail Risk (95%)		
	Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value	
$\hat{\gamma}^{EST} \times \hat{\beta}^{ESE}$	-0.03	-4.79	***	-0.04	-5.40	***	-0.04	-4.93	***
$\hat{\gamma}^{SST} \times \hat{\beta}^{SSE}$	-0.04	-4.52	***	-0.05	-5.21	***	-0.05	-4.73	***
$\hat{\gamma}^{GST} \times \hat{\beta}^{GSE}$	-0.02	-3.33	***	-0.03	-4.76	***	-0.03	-3.36	***
$\hat{\gamma}^{Investor}$	-0.05	-5.27	***	-0.05	-7.37	***	-0.04	-6.27	***
Return	-0.03	-3.52	***	-0.03	-4.61	***	-0.04	-4.97	***
Stdev.				0.39	4.34	***	0.37	5.73	***
Incentive fee	-0.02	-2.16	**	-0.05	-4.48	***	-0.06	-3.98	***
High water mark	-0.04	-5.86	***	-0.07	-5.23	***	-0.04	-5.12	***
Onshore	-0.03	-3.42	***	-0.03	-4.80	***	-0.03	-4.87	***
Leveraged	-0.12	-3.17	***	-0.04	-3.88	***	-0.01	-3.69	***
Log(Assets)	-0.06	-2.67	***	-0.15	-7.90	***	-0.07	-4.60	***
Controlled lower-order terms	Y			Y			Y		
Style	Y			Y			Y		
Fund–Firm	Y			Y			Y		
Year	Y			Y			Y		
Num. of Obs.	189,164			118,527			118,527		
Adj. R^2	5.90%			7.14%			6.28%		

Table 5. ESG Pillar Sentiment Exposures, Timing Skills, and Hedge Fund Alphas

This table presents 5×5 portfolio sorts of funds by ESG pillar sentiment exposures and timing skills. The pillar exposures and two types of pillar-level sentiment timing abilities (Henriksson and Merton, 1981, adjusted by Goetzmann et al., 2000 [HM-GII], and Cao et al., 2013 [CCLL]) are estimated using the following equations:

$$\begin{aligned} Excess\ Return_{it} &= \alpha_t + \beta_{it}^{XSE}\Delta Sentiment_t^X + \gamma_{it}^{XST;\,CCLL} MKT_{it}(\Delta Sentiment_t^X - \overline{\Delta Sentiment_{t-36}^X}) + \theta' f_t \\ &+ \sum_{j=1}^{S_i-1}\rho_j StyleDummies_j + \sum_{q=1}^{Y_i-1}\eta_q YearDummies_{qi} + \varepsilon_t \end{aligned}$$

$$\begin{aligned} Excess\ Return_{it} &= \alpha_t + \beta_{it}^{XSE;\,HM\&GII}(\Delta Sentiment_t^X - \overline{\Delta Sentiment_{t-36}^X}) + \gamma_{it}^{XST;\,HM\&GII}\ max(0, \Delta Sentiment_t^X \\ &- \overline{\Delta Sentiment_{t-36}^X}) + \theta' f_t + \sum_{j=1}^{S_i-1}\varphi_j StyleDummies_j + \sum_{q=1}^{Y_i-1}\eta_q YearDummies_{qi} + \varepsilon_t \end{aligned}$$

In each equation, X denotes the ESG pillars (Environment, Social, or Governance). β_{it}^{XSE} represents the pillar sentiment exposure for fund i at month t. $\gamma_{it}^{XST;\,CCLL}$ and $\gamma_{it}^{XST;\,HM}$ represent two measures of sentiment timing skills.[29] $\Delta Sentiment_{it}^X$ represents the changes of the pillar sentiment indices ($\Delta Sentiment_t^X = Sentiment_t^X - Sentiment_t^X$), and the term $\overline{\Delta Sentiment_{t-36}^X}$ denotes its 36-month rolling average. Y_i and S_i represent the total number of years and styles for fund i. f_t represents the nine hedge fund factors selected by Chen et al. (2025).[30] TASS style and year dummies are included in the regression, along with clustered standard errors for both style and year.

All funds are ranked from 1 (lowest) to 5 (highest) based on their pillar sentiment exposures and timing skills. Each cell reports the average alpha (%, Chen et al., 2025) for the corresponding quintile portfolios. Panel A reports portfolio results for pillar exposures and CCLL timing skills, while Panel B reports results for pillar exposures and HM timing skills. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

[29] For $\gamma_{it}^{XST;\,HM}$,we measured using the timing skill measurement developed by Henriksson and Merton (1981), with the consideration of daily cumulative timing opportunities underscored by Goetzmann, Ingersoll, and Ivkovic (2000).

[30] We get the data from Yong Chen's website: https://sites.google.com/site/yongchenfinance/.

Panel A: Pillar Exposures, HM-GII adjusted Timing Skills, and Average Monthly Alphas (%)								
		Panel B1: Environment						
		Exposures						
		1 (bottom)	2	3	4	5 (top)	Top-Bottom	
Timing	1 (bottom)	0.01	0.01	0.02	0.04	0.04	0.03	***
	2	0.01	0.02	0.03	0.06	0.05	0.04	***
	3	0.02	0.03	0.05	0.06	0.10	0.08	***
	4	0.03	0.06	0.09	0.11	0.15	0.12	***
	5 (top)	0.05	0.10	0.12	0.18	0.20	0.16	***
	Top-Bottom	0.04	0.09	0.10	0.14	0.16		
		***	***	***	***	***		
		Panel B2: Social						
		Exposures						
		1 (bottom)	2	3	4	5 (top)	Top-Bottom	
Timing	1 (bottom)	0.01	0.01	0.02	0.02	0.04	0.03	***
	2	0.01	0.02	0.03	0.06	0.08	0.07	***
	3	0.02	0.02	0.06	0.08	0.11	0.10	***
	4	0.03	0.04	0.10	0.14	0.20	0.17	***
	5 (top)	0.05	0.08	0.15	0.20	0.29	0.23	***
	Top-Bottom	0.05	0.07	0.13	0.18	0.25		
		***	***	***	***	***		
		Panel B3: Governance						
		Exposures						
		1 (bottom)	2	3	4	5 (top)	Top-Bottom	
Exposures	1 (bottom)	0.01	0.01	0.02	0.04	0.04	0.03	***
	2	0.01	0.01	0.02	0.05	0.06	0.05	***
	3	0.02	0.02	0.05	0.10	0.11	0.08	***
	4	0.03	0.05	0.09	0.12	0.13	0.10	***
	5 (top)	0.06	0.08	0.13	0.16	0.17	0.11	***
	Top-Bottom	0.05	0.08	0.11	0.12	0.13		
		***	***	***	***	***		

Panel B: Pillar Exposures, CCLL Timing Skills, and Average Monthly Alphas (%)

Panel A1: Environment

		Exposures						
		1 (bottom)	2	3	4	5 (top)	Top-Bottom	
Timing	1 (bottom)	0.01	0.01	0.02	0.04	0.04	0.03	***
	2	0.01	0.01	0.02	0.05	0.06	0.05	***
	3	0.02	0.02	0.05	0.10	0.11	0.08	***
	4	0.03	0.05	0.09	0.12	0.13	0.10	***
	5 (top)	0.06	0.08	0.13	0.16	0.17	0.11	***
	Top-Bottom	0.05	0.08	0.11	0.12	0.13		
		***	***	***	***	***		

Panel A2: Social

		Exposures						
		1 (bottom)	2	3	4	5 (top)	Top-Bottom	
Timing	1 (bottom)	0.01	0.01	0.02	0.02	0.03	0.02	***
	2	0.01	0.01	0.03	0.05	0.07	0.06	***
	3	0.02	0.03	0.05	0.08	0.12	0.10	***
	4	0.03	0.05	0.08	0.13	0.16	0.12	***
	5 (top)	0.04	0.06	0.12	0.18	0.23	0.19	***
	Top-Bottom	0.03	0.05	0.11	0.16	0.20		
		***	***	***	***	***		

Panel A3: Governance

		Exposures						
		1 (bottom)	2	3	4	5 (top)	Top-Bottom	
Exposures	1 (bottom)	0.01	0.02	0.03	0.05	0.05	0.03	***
	2	0.03	0.03	0.04	0.07	0.07	0.04	***
	3	0.04	0.04	0.05	0.07	0.10	0.06	***
	4	0.04	0.06	0.09	0.13	0.12	0.07	***
	5 (top)	0.06	0.11	0.12	0.15	0.16	0.10	***
	Top-Bottom	0.05	0.09	0.10	0.11	0.12		
		***	***	***	***	***		

Table 6 Significant Pillar Sentiment Exposures and Timing Skills Summary Statistics and Across Fund Strategies

This table reports summary statistics for significant ESG pillar sentiment exposures and timing skills, both overall and by fund strategy. Panel A presents the percentage of statistically significant (at the 10% level or better) ESG pillar exposures and timing skills. Panel B shows the number and percentage of significant timing skills across directional, semi-directional, and non-directional strategies, following the classification in Bali et al. (2014). Panel C reports the mean exposures and timing skills for each strategy group.

Panel A: Significant ESG Pillar Exposures and Timing Skills Among Hedge Funds

	Significant Exposure (% of all funds)	Significant Timing Ability (% among those with significant exposure)	Total Num of Funds
Environment	40.33%	68.23%	
Social	37.81%	65.06%	4,557
Governance	36.67%	65.01%	

Panel B: Total Number and Percentage of Significant Pillar Timing Skills Across Strategies

	Total Num. of Funds	Directional (in %)	Semi-directional (in %)	Nondirectional (in %)
Environment	1,407	33.12%	27.40%	27.27%
Social	281	34.90%	29.54%	25.73%
Governance	1,232	37.74%	21.71%	24.92%

Panel C: Mean Exposures and Timing Skills Across Strategies

	Mean Exposures			Mean Timing Skill		
	Environment	Social	Governance	Environment	Social	Governance
Directional	0.47	0.42	0.26	0.58	0.60	0.29
Semi-directional	0.33	0.42	0.25	0.39	0.43	0.31
Nondirectional	0.02	0.02	0.01	0.03	0.03	0.02

Table 7 Average Pillar Sentiment Timing Skills Across Different Measurement Methods

This table reports the average pillar sentiment timing skills across two alternative measurement approaches: Henriksson and Merton (1981, [HM]) and Goetzmann et al. (2000, [CCLL]), for the Environmental (Panel A), Social (Panel B), and Governance (Panel C) pillars. In each panel, "High/Low" indicates whether a fund's timing skill is above or below the cross-sectional average, based on the CCLL measure (Cao et al., 2013). Each cell shows the average timing skill for statistically significant funds (at the 10% level or better) using the HM and CCLL methods, across directional, semi-directional, and non-directional funds classified according to Bali et al. (2014).

	Panel A: Environment Timing (CCLL)		
	High	Low	Model
Directional	0.87	0.24	HM
	0.90	0.26	GII
Semidirectional	0.74	0.13	HM
	0.82	0.18	GII
Nondirectional	0.53	-0.08	HM
	0.65	0.00	GII
	Panel B: Social Timing (CCLL)		
	High	Low	Model
Directional	0.85	0.22	HM
	0.90	0.24	GII
Semidirectional	0.47	0.18	HM
	0.74	0.19	GII
Nondirectional	0.43	-0.10	HM
	0.44	0.00	GII
	Panel C: Governance Timing (CCLL)		
	High	Low	Model
Directional	0.28	0.18	HM
	0.30	0.21	GII
Semidirectional	0.23	0.12	HM
	0.24	0.16	GII
Nondirectional	0.03	-0.06	HM
	0.10	0.00	GII

Table 8 ESG and Pillar Sentiment Timing Skills Predicting Fund Flow

This table presents fund flow predictions by using pillar sentiment timing skills, according to the equation below[31]

$$Flow_{it} = \alpha_{it} + \sum_{X\in\{E,S,G\}}[\delta_{HTT}\, High\, Trank_{t-1} \times \hat{\gamma}_{it-1}^{XST} + \delta_{MTT} Mid\, Trank_{t-1} \times \hat{\gamma}_{it-1}^{XST} + \delta_{LTT} Low\, Trank_{t-1} \times \hat{\gamma}_{it-1}^{XST} + \delta_{XST}\hat{\gamma}_{it-1}^{XST}] + \delta_{Investor}\hat{\gamma}_{it-1}^{Investor} + \delta_{HT} High\, Trank_{t-1} + \delta_{MT} Mid\, Trank_{t-1} + \delta_{LT} Low\, Trank_{t-1} + \delta_M Management\ Fee_{t-1} + CFlow_{t-1}^{\prime\delta_{CFlow}} + \sum_{j=1}^{14}\rho_j StyleDummies_j + \sum_{q=1}^{11}\eta_q YearDummies_{qi} + \sum_{f=1}^{1487}\varphi_f FirmDummies_{qi} + \varepsilon_{it}$$

X denotes the ESG pillars (Environment, Social, or Governance). $\hat{\gamma}_{it-1}^{XST}$ is the estimated pillar timing skills (CCLL) for fund i in month $t-1$. $\hat{\gamma}_{it-1}^{Investor}$ is the investor sentiment timing skill, measured by the sensitivity of fund i's excess return to detrended pillar sentiment changes, condition on the market equity factor (Cao et al., 2013). All models in this table use TASS style, year, and firm dummies, along with clustered standard errors for style, year, and fund-firm pairs. The lower order terms are controlled within all models ($\hat{\gamma}_{it-1}^{XST}$). ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Coef.	*t*-Value	
High Trank*$\hat{\gamma}^{EST}$	0.05	5.10	***
Mid Trank*$\hat{\gamma}^{EST}$	0.04	5.06	***
Low Trank*$\hat{\gamma}^{EST}$	0.02	3.00	***
High Trank*$\hat{\gamma}^{SST}$	0.05	4.98	***
Mid Trank*$\hat{\gamma}^{SST}$	0.04	3.46	***
Low Trank*$\hat{\gamma}^{SST}$	0.03	2.23	**
High Trank*$\hat{\gamma}^{GST}$	0.04	3.52	***
Mid Trank*$\hat{\gamma}^{GST}$	0.03	2.47	**
Low Trank*$\hat{\gamma}^{GST}$	0.02	2.10	**
$\hat{\gamma}^{Investor}$	0.07	5.19	***
High Trank	0.28	6.72	***
Mid Trank	-0.14	-4.58	***
Low Trank	-0.49	-5.06	***
Stdev.	-0.07	-2.16	**
Management fee	0.15	2.84	***
Incentive fee	0.01	2.17	**
High water mark	0.22	2.58	***
Onshore	0.03	2.01	**
Leveraged	0.02	2.88	***
Log(Assets)	0.12	6.84	***
Controlled lower-order terms	Y		
Style	Y		
Firm	Y		
Year	Y		
Num. of Obs.	114634		
Adj. R^2	15.71%		

31 $Flow_{it} = \frac{Assets_{i,t} - Assets_{i,t-1}*(1+Return_{i,t})}{Assets_{i,t-1}}$. *High rank*, *Mid rank,* and *Low rank* are computed as $Min(\frac{1}{3}, Frank_{it-1})$, $Min(\frac{1}{3}, Frank_{it-1} - High\, Trank_{it-1})$, and $Min(\frac{1}{3}, Frank_{it-1} - High\, Trank_{it-1} - Mid\, Trank_{it-1})$ respectively (Liang et al., 2019). Where $Frank_{it-1}$ is the fractional rank for funds from 0 to 1, according to their average monthly return in the previous year.
$CFlow_{t-1}$ represents a vector of variables, including standard deviation of monthly returns, leveraged or not, onshore, and high-water mark indicators, log of assets, incentive fee, and fund management fee in year t−1.

Table 9 Fund Assets Instruments and Focus Details Predicting ESG Pillar Timing Skills

This table presents ESG pillar timing skills predictions using LASSO regression, as specified in the equation below.[32]

$$\min_{\beta_j} \sum_{i=1}^{n}\left(\hat{\gamma}_t^{XST} - \sum_{j=1}^{p} \boldsymbol{X}_{\boldsymbol{AFI}\ \boldsymbol{t-1,j}} \boldsymbol{\beta}_{\boldsymbol{AFI}\ \boldsymbol{t-1,j}}\right)^2 + \lambda \sum_{j=1}^{p}|\beta_j|$$

$\hat{\gamma}_{it-1}^{XST}$ is the estimated pillar timing skills (CCLL) for fund i in month $t-1$. $\boldsymbol{X}_{\boldsymbol{AFI}}$ includes 129 variables capturing asset allocation, geographic and sector focus, investment focus, and approach. Results rank variables by the magnitude of their absolute coefficients.

Panel A: Environment		
	Coef.	Rank
Geographic Focus: Western Europe	4.18	1
Investment Focus: Socially Responsible	3.04	2
Asset Commodities: Softs	2.84	3
Sector Focus: Shipping	2.84	4
Asset Commodities: Base Metals	2.82	5
Sector Focus: Biotechnology	2.72	6
Asset Commodities: Agriculturals	2.49	7
Sector Focus: Natural Resources	2.34	8
Sector Focus: Gold	2.29	9
Geographic Focus: Russia	2.24	10
Panel B: Social		
	Coef.	Rank
Investment Approach: Directional	6.70	1
Investment Focus: Shareholder Activist	4.20	2
Sector Focus: Health Care	3.27	3
Geographic Focus: Western Europe	2.18	4
Investment Focus: Socially Responsible	2.12	5
Asset Commodities: Primary Focus	2.07	6
Geographic Focus: Latin America	2.05	7
Investment Approach: Short Bias	1.96	8
Sector Focus: Media Communications	1.89	9
Sector Focus: Private Equity	1.84	10
Panel C: Governance		
	Coef	Rank
Sector Focus: Corporate Bonds	2.16	1
Asset Equities: Equities	1.99	2
Investment Focus: Bankruptcy	1.70	3
Sector Focus: Pure Currency	1.49	4
Sector Focus: Micro Cap	1.47	5
Sector Focus: Government Bonds	1.46	6
Sector Focus: Sovereign Debt	1.44	7
Sector Focus: Turnarounds Spin Offs	1.42	8
Investment Approach: Bottom Up	1.35	9
Investment Focus: Pairs Trading	-1.35	10

[32] λ is the tunning parameter, which is optimally found by choosing the value that returns us to the smallest MSE according to the 10-fold cross-validation for the LASSO regression. p is the number of the parameters that equals to 130 (129+1 intercept).

Appendix

Table 1 Variable Explanation

This table presents detailed variable explanations for TASS variables (Panel A), ESG sentiment variables (Panel B), ESG sentiment betas, non-TASS indicators used in the empirical models (Panel C), and policy indicators (Panel D)

Panel A: TASS Variables	
Variables	Explanations
Age	Number of survival years since inception.
Appraisal ratio (36m)	36-month rolling appraisal ratio.
Assets ($M)	Assets in millions.
CLTZ HF9 Alpha (36m)	36-month rolling hedge fund 9-factor alpha, introduced by Chen, Li, Tang, and Zhou (2025).
Expected Shortfall (95%)	36-month rolling 95% expected shortall.
High Water Mark	Whether the fund has a high-water mark or not.
Incentive fee	Incentive fee of a fund.
Kurtosis	36-month rolling kurtosis.
Leveraged	Whether the fund is leveraged or not.
Lock up Period	Lockup period in days.
Management fee	Management Fee of a fund.
Margin	Whether the fund use margin or not.
Min. Investment ($M)	Minimum Investment in millions.
Onshore	Whether the fund is domiciled in the US or not.
Red. Freq.	Redemption frequency in days
Return	Monthly rate of return.
Sortino ratio	36-month rolling Sortino Ratio.
Skewness	36-month rolling skewness.
Stdev.	36-month rolling standard deviations.
Sub. Freq.	Subscription frequency in days.
Tail risk (95%)	36-month rolling 95% tail risk.
Panel B: ESG Sentiment Variables	
Variables	Explanations
Access Affordability	Products and services as inexpensive and accessible net of references to being overpriced or exclusive.
Accounting Sentiment	Positive versus negative perceptions of accounting practices.
Airborne Emissions Improvement	Companies' progress towards reducing GHG, particulate and other emissions net of references to increases.

Carbon Emissions Improvement	Companies' progress towards reducing GHG, particulate and other emissions net of references to increases.
Climate Policy	Company policies to reduce GHG, particulate and other emissions net of references to policy violations.
Customer Satisfaction	Satisfied customers net of references to dissatisfied customers.
Diversity Efforts	Promoting equal opportunities, minority promotions, and diversity in the workplace net of references to discrimination and lack of opportunity based on gender, ethnicity, or national origin.
Energy Efficiency Efforts	Energy efficiency net of references to energy waste.
Management Diversity	Management racial, ethnic, sexual orientation, and gender diversity net of references to uniformity.
Management Sentiment	Positive statements about corporate management net of negative.
Management Trust	Overall trusting statements about corporate management net of mistrustful comments.
Pollution Improvement	Companies' improvements in polluting waste net of references to expansion in polluting waste.
Privacy Efforts	Data security and privacy net of references to violations.
Product Sentiment	General products and services in a positive tone, net of a negative tone.
Public Health Support	Companies' products, services, or activities in support of public health net of references to harm to public health.
Shareholders	Companies' effectiveness towards equal treatment of shareholders and the use of anti-takeover devices as well as shareholder and financial controversies at a company.
Supply Chain Sustainability	Supply chain sustainability net of references to unsustainable practices in the supply chain.
Sustainability Improvement	Growth in sustainable corporate activities net of reference to unsustainable practices.
Trust	Trusting net of mistrustful comments.
Wage Fairness	Wage fairness net of references to pay disparities.
Workplace Development	Abundant training and development opportunities net of limited training and development activities.
Workplace Safety Efforts	The work environment as healthy and safe net of reference to unhealthy or exploitative working conditions.
Workplace Sentiment	Positive perceptions of the workplace and working environment net of negative.

Panel C: ESG Sentiment Betas, Indicators, and Policies

Variables	Explanations
β^{ESE}	Environmental pillar sentiment beta.
β^{SSE}	Social pillar sentiment Beta.
β^{GSE}	Governance pillar sentiment beta.
γ^{EST}	Environmental pillar sentiment timing skill.
γ^{SST}	Social pillar sentiment timing skill.
γ^{GST}	Governance pillar sentiment timing skill.

GDPR	Whether the date is after the General Data Protection Regulation (GDPR) entered into force (05/25/2018).
Paris Agreement	Whether the date is after the Paris Agreement entered into force (11/04/2016).
Panel D: Other Control Variables	
Variables	Explanations
Bankruptcy	Bankruptcy topic index developed by Bybee, Kelly, Manela, and Xiu (2024).
Corrections/amplifications	Corrections or amplifications topic index developed by Bybee, Kelly, Manela, and Xiu (2024).
Diseases	Diseases topic index developed by Bybee, Kelly, Manela, and Xiu (2024).
Environment	Natural disasters topic index developed by Bybee, Kelly, Manela, and Xiu (2024).
Gender Issues	Gender issues topic index developed by Bybee, Kelly, Manela, and Xiu (2024).
High trank	Calculated by $Min(\frac{1}{3}, Frank)$, where $Frank$ is the fractional rank for funds from 0 to 1, according to their average historical return in the relative year.
Low trank	Calculated by $Min(\frac{1}{3}, Frank - High\ trank - Mid\ trank)$, where $Frank$ is the fractional rank for funds from 0 to 1, according to their average historical return in the relative year.
Mid trank	Calculated by $Min(\frac{1}{3}, Frank - High\ trank)$, where $Frank$ is the fractional rank for funds from 0 to 1, according to their average historical return in the relative year.
Natural Disasters	Natural disasters topic index developed by Bybee, Kelly, Manela, and Xiu (2024).

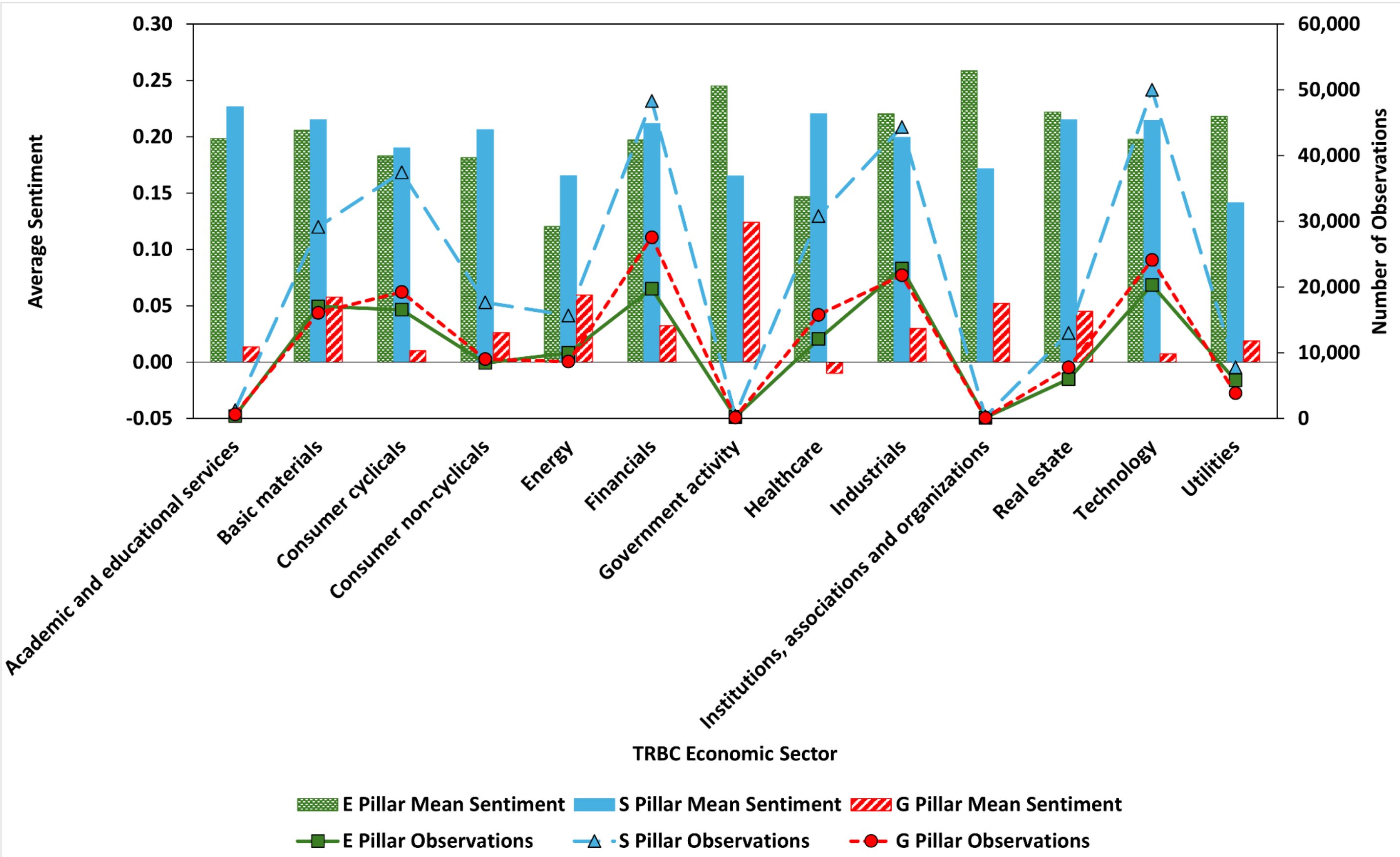
Table 2 Descriptive Statistics for Fund Assets Instruments and Focus Details

This table presents the minimum, mean, median, maximum, and standard deviation for fund-level asset allocation, sector focus, investment approach, global focus, and investment focus indicators provided by TASS at the fund level.

Type	Variables	N	Min	Mean	Median	Max	Stdev.
Asset Equities	Equities	1,933	0.00	0.79	1.00	1.00	0.41
Asset Commodities	Agriculturals	1,933	0.00	0.09	0.00	1.00	0.29
	Base Metals	1,933	0.00	0.08	0.00	1.00	0.27
	Softs	1,933	0.00	0.07	0.00	1.00	0.25
Sector Focus	Corporate Bonds	4,543	0.00	0.05	0.00	1.00	0.22
	Gold	4,543	0.00	0.02	0.00	1.00	0.15
	Government Bonds	4,543	0.00	0.04	0.00	1.00	0.20
	Health Care	4,543	0.00	0.04	0.00	1.00	0.20
	Media Communications	4,543	0.00	0.04	0.00	1.00	0.20
	Micro Cap	4,543	0.00	0.03	0.00	1.00	0.16
	Natural Resources	4,543	0.00	0.04	0.00	1.00	0.19
	Private Equity	4,543	0.00	0.01	0.00	1.00	0.11
	Shipping	4,543	0.00	0.02	0.00	1.00	0.15
	Sovereign Debt	4,543	0.00	0.03	0.00	1.00	0.16
	Turnarounds Spin Offs	4,543	0.00	0.03	0.00	1.00	0.17
Investment Approach	Bottom Up	4,543	0.00	0.21	0.00	1.00	0.40
	Relative Value	4,543	0.00	0.12	0.00	1.00	0.33
	Short Bias	4,543	0.00	0.17	0.00	1.00	0.37
Geographic Focus	Latin America	4,543	0.00	0.37	0.00	1.00	0.48
	Russia	4,543	0.00	0.02	0.00	1.00	0.14
	Western Europe	4,543	0.00	0.08	0.00	1.00	0.26
Investment Focus	Bankruptcy	4,543	0.00	0.02	0.00	1.00	0.14
	PairsTrading	4,543	0.00	0.04	0.00	1.00	0.19
	Shareholder Activist	4,543	0.00	0.01	0.00	1.00	0.11
	Socially Responsible	4,543	0.00	0.00	0.00	1.00	0.06

Figure 1 Sector Mean Pillar Sentiments

This figure illustrates the average environmental, social, and governance sentiment across firms' TRBC sectors (as defined by LSEG), based on LSEG MarketPsych ESG Analytics data from January 2003 to December 2024.[33] The green (environment), blue (social), and red (governance) bars represent the average pillar sentiments for firms in each sector (left y-axis). The green solid (environment), blue long-dashed (social), and red dashed (governance) lines indicate the total number of observations for the respective variables (right y-axis).



[33] The net sentiment variables range from -1 to 1, include 7 environmental, 11 social, and 5 governance variables.

Figure 2 Pillar Sentiment and Topic Indices

This figure compares pillar sentiment indices with topic indices from Bybee et al. (2024). Figure 2A compares environmental sentiment with Environment and Natural Disasters. Figure 2B compares social sentiment with Gender Issues and Diseases. Figure 2C compares governance sentiment with Bankruptcy and Corrections/Amplifications.

Figure 2A Environmental Pillar, Natural Disasters, and Environment Topic Indices

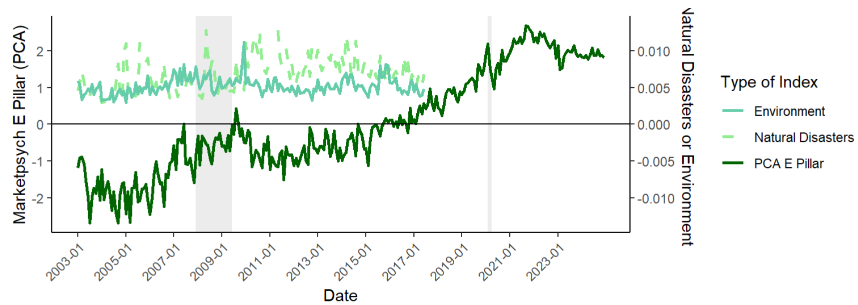


Figure 2B Social Pillar, Gender Issues, and Diseases Topic Indices

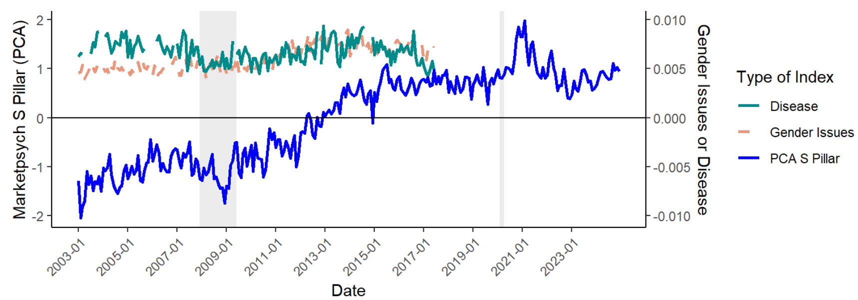


Figure 2C Governance Pillar, Bankruptcy, and Corrections/Amplifications Topic Indices

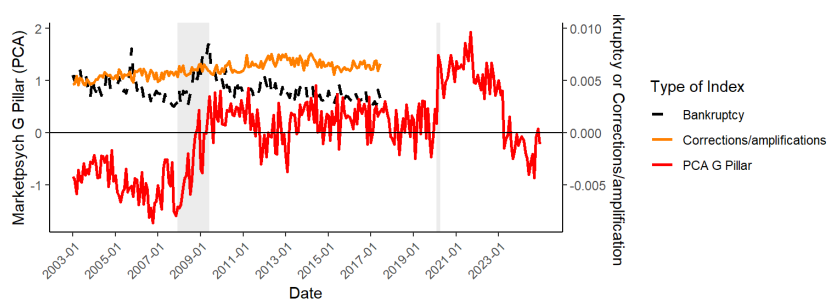


Table 3 Pillar Sentiment Betas and Topic Indices Predicting Performance and Risks

This table presents the prediction of funds' future performance and risks[34] using environmental (Panel A), social (Panel B), and governance (Panel C) pillar sentiment timing skills, while controlling for the topic indices from Engle et al. (2020)[EGLKS], Ardia et al. (2023)[ABBI], and Bybee et al. (2024) (Environment, Natural Disasters, Gender Issues, Diseases, Bankruptcy, and Corrections/Amplifications). Panels A, B, and C use the model presented below, respectively.

$$Sortino\ Ratio_{it}\ or\ Appraisal\ Ratio_{it}\ or\ CLTZ\ HF9\ Alpha_{it}\ or\ Stdev._{it}\ or\ Tail\ risk_{95\%,it}\ or\ Expected\ shortfalls_{95\%,it}\ or\ Flow_{it} = \alpha_{it} + \delta_{SigEST}\hat{\gamma}^{EST}_{it-1}\mathbf{1}(Significant\ \hat{\gamma}^{EST}_{it-1}) + \delta_E\hat{\gamma}^{EST}_{it-1} + \delta_{Sig}\mathbf{1}(Significant\ \hat{\gamma}^{EST}_{it-1}) + \delta_{Env}Environemt_{t-1} + \delta_{NatD}Natural\ Disasters_{t-1} + C'^{\delta_C}_{t-1} + \sum_{j=1}^{14}\gamma_j StyleDummies_j + \sum_{q=1}^{11}\eta_q YearDummies_{qi} + \sum_{f=1}^{1487}\varphi_f FirmDummies_{qi} + \varepsilon_{it}$$

$$Sortino\ Ratio_{it}\ or\ Appraisal\ Ratio_{it}\ or\ CLTZ\ HF9\ Alpha_{it}\ or\ Stdev._{it}\ or\ Tail\ risk_{95\%,it}\ or\ Expected\ shortfalls_{95\%,it} or\ Flow_{it} = \alpha_{it} + \delta_{SigSST}\hat{\gamma}^{SST}_{it-1}\mathbf{1}(Significant\ \hat{\gamma}^{SST}_{it-1}) + \delta_S\hat{\gamma}^{SSt}_{it-1} + \delta_{Sig}\mathbf{1}(Significant\hat{\gamma}^{SSt}_{it-1}) + \delta_{Gender}Gender\ Issues_{t-1} + \delta_{Diseases}Diseases_{t-1} + C'^{\delta_C}_{t-1} + \sum_{j=1}^{14}\gamma_j StyleDummies_j + \sum_{q=1}^{11}\eta_q YearDummies_{qi} + \sum_{f=1}^{1487}\varphi_f FirmDummies_{qi} + \varepsilon_{it}$$

$$Sortino\ Ratio_{it}\ or\ Appraisal\ Ratio_{it}\ or\ CLTZ\ HF9\ Alpha_{it}\ or\ Stdev._{it}\ or\ Tail\ risk_{95\%,it}\ or\ Expected\ shortfalls_{95\%,it}\ or\ Flow_{it} = \alpha_{it} + \delta_{SigGST}\hat{\gamma}^{GST}_{it-1}\mathbf{1}(Significant\ \hat{\gamma}^{GST}_{it-1}) + \delta_G\hat{\gamma}^{GSt}_{it-1} + \delta_{Sig}\mathbf{1}(Significant\hat{\gamma}^{SSt}_{it-1}) + \delta_{Bankt.}Bankruptcy_{t-1} + \delta_{Correct.}Corrections/amplifications_{t-1} + C'^{\delta_C}_{t-1} + \sum_{j=1}^{14}\gamma_j StyleDummies_j + \sum_{q=1}^{11}\eta_q YearDummies_{qi} + \sum_{f=1}^{1487}\varphi_f FirmDummies_{qi} + \varepsilon_{it}$$

$\mathbf{1}(Significant\ \hat{\gamma}^{XST}_{it-1})$ is a binary variable that equals 1 if the funds' estimated 36-month ESG timing skills at time $t-1$ is statistically significant at the 10% level (X represents E, S, or G pillar). All models in this table use TASS style, year, and firm dummies, along with clustered standard errors for style, year, and firm. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

[34] The CLTZ HF9 alpha for each fund is calculated by $Excess\ Return_t = \alpha_t + \theta' f_t + \varepsilon_t$. $Excess\ Return_t$ is calculated by using a fund's monthly return minus the 3-month US Treasury Bill return at month t. $Stdev.$ is the rolling 36-month standard deviations. Sortino ratio is calculated by $\frac{Excess\ Return}{Stdev.(R_{ret<Tar})}$ in a rolling 36-month window. $Stdev.(R_{ret<Tar})$ is the standard deviation of the monthly returns that are smaller than the 3-month US Treasury Bill returns in the related months.
The rolling appraisal ratio is calculated by regressing the 36 months excess returns of fund i on the excess return of the fund's TASS-style index j within the same year (BGLS, 2008). Specifically, $r_{it} - R_{ft} = \alpha_{it} + \beta_i(r_{jt} - R_{ft}) + \varepsilon_{it}$, where R_{ft} is the 3-month US Treasury Bill return. The appraisal ratio is calculated as α_{it} devided by standard deviation of the residuals (ε_{it}).
According to Liang and Park (2010), the 95% expected shortfall is calculated by $ES_t(95\%,\tau) = -E_t[R_{t+\tau}|R_{t+\tau} \leq -VaR_t(95\%,\tau)]$, and the tail risks is calculated by $Tail\ risk_{95\%} = \sqrt{E_t[(R_{t+\tau} - E_t(R_{t+\tau}))^2|R_{t+\tau} \leq -VaR_t(95\%,\tau)]}$. $R_{t+\tau}$ is the portfolio return during the period from t to $t+\tau$. Both are calculated using a rolling 36-month window.
$Flow_{it} = \frac{Assets_{i,t} - Assets_{i,t-1} * (1+Return_{i,t})}{Assets_{i,t-1}}$.

Panel A: Environment Pillar												
Performance												
	CLTZ HF9 Alpha			Sharpe Ratio			Appraisal Ratio			Sortino Ratio		
	Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value	
$\hat{\gamma}^{EST}$ ×												
1 (Significant $\hat{\gamma}^{EST}$)	0.31	8.84	***	0.08	8.08	***	0.08	8.59	***	0.25	8.98	***
EGLKS	0.26	5.46	***	0.05	6.81	***	0.03	6.63	***	0.24	7.87	***
ABBI	0.34	6.02	***	0.04	6.37	***	0.04	6.87	***	0.25	6.24	***
Natural Disasters (BKMX)	-0.29	6.61	***	-0.07	-7.51	***	-0.03	-4.78	***	-0.23	-7.49	***
Environment (BKMX)	0.38	7.30	***	0.05	6.49	***	0.04	6.36	***	0.14	7.29	***
Style	Y			Y			Y			Y		
Firm	Y			Y			Y			Y		
Year	Y			Y			Y			Y		
Num. of Obs.	116,701			116,611			32,263			116,701		
Adj. R^2	6.22%			5.71%			5.37%			7.22%		
Risks and Fund Flows												
	Stdev.			Tail Risk			95% Expected Shortfall			Fund Flow		
	Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value	
$\hat{\gamma}^{EST}$ ×												
1 (Significant $\hat{\gamma}^{EST}$)	-0.29	-8.04	***	-0.23	-8.87	***	-0.38	-8.24	***	0.36	7.38	***
EGLKS	-0.25	-7.09	***	-0.23	-7.62	***	-0.26	-2.82	***	0.22	5.68	***
ABBI	-0.26	-6.53	***	-0.23	-7.25	***	-0.27	-4.17	***	0.22	5.49	***
Natural Disasters (BKMX)	0.24	7.31	***	0.21	7.77	***	0.25	5.72	***	-0.24	6.21	***
Environment (BKMX)	-0.25	-6.78	***	-0.20	1.98	**	-0.23	-6.50	***	0.25	6.96	***
Style	Y			Y			Y			Y		
Firm	Y			Y			Y			Y		
Year	Y			Y			Y			Y		
Num. of Obs.	117,046			116,611			116,611			114,035		
Adj. R^2	6.53%			6.86%			6.28%			5.84%		

Panel B: Social Pillar												
Performance												
	CLTZ HF9 Alpha			Sharpe Ratio			Appraisal Ratio			Sortino Ratio		
	Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value	
$\hat{\gamma}^{SST} \times$												
1 (Significant $\hat{\gamma}^{SST}$)	0.38	8.28	***	0.08	8.02	***	0.09	7.90	***	0.35	8.26	***
Gender Issues	0.28	6.61	***	0.06	2.62	***	0.04	5.56	***	0.20	6.71	***
Diseases	-0.34	-7.78	***	-0.06	-5.61	***	-0.06	-6.49	***	-0.22	-7.00	***
Style	Y			Y			Y			Y		
Firm	Y			Y			Y			Y		
Year	Y			Y			Y			Y		
Num. of Obs.	95,477			66,803			20,357			95,477		
Adj. R^2	6.20%			5.80%			5.25%			7.20%		
Risks and Fund Flows												
	Stdev.			Tail Risk			95% Expected Shortfall			Fund Flow		
	Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value		Coef.	*t*-Value	
$\hat{\gamma}^{SST} \times$												
1 (Significant $\hat{\gamma}^{SST}$)	-0.30	-7.19	***	-0.04	-9.10	***	-0.28	-7.04	***	0.44	6.01	***
Gender Issues	-0.17	-6.97	***	0.04	5.64	***	-0.13	-2.33	**	0.37	3.06	***
Diseases	0.19	6.86	***	0.01	0.28		0.25	6.66	***	-0.42	-5.41	***
Style	Y			Y			Y			Y		
Firm	Y			Y			Y			Y		
Year	Y			Y			Y			Y		
Num. of Obs.	67,176			66,803			66,803			65,199		
Adj. R^2	6.91%			6.83%			6.27%			5.56%		

Panel C: Governance Pillar												
	Performance											
	CLTZ HF9 Alpha			Sharpe Ratio			Appraisal Ratio			Sortino Ratio		
	Coef.	t-Value		Coef.	t-Value		Coef.	t-Value		Coef.	t-Value	
$\hat{\gamma}^{GST}$ ×												
1 (Significant $\hat{\gamma}^{GST}$)	0.07	4.77	***	0.02	6.61	***	0.06	7.86	***	0.05	4.08	***
Bankruptcy	-0.05	-3.99	***	-0.02	-6.56	***	-0.06	-7.81	***	-0.03	-3.05	***
Corrections/amplifications	-0.02	-3.44	***	-0.02	-5.77	***	-0.03	-2.42	**	-0.01	-2.58	**
Style	Y			Y			Y			Y		
Firm	Y			Y			Y			Y		
Year	Y			Y			Y			Y		
Num. of Obs.	95,477			66,803			20,357			95,477		
Adj. R^2	6.16%			5.77%			5.21%			7.16%		
	Risks and Fund Flows											
	Stdev.			Tail Risk			95% Expected Shortfall			Fund Flow		
	Coef.	t-Value		Coef.	t-Value		Coef.	t-Value		Coef.	t-Value	
$\hat{\gamma}^{GST}$ ×												
1 (Significant $\hat{\gamma}^{GST}$)	-0.08	-5.38	***	-0.01	-3.13	***	-0.27	-6.76	***	0.08	5.82	***
Bankruptcy	0.08	4.25	***	0.10	0.78		0.16	3.13	***	-0.07	-4.81	***
Corrections/amplifications	0.05	2.37	**	0.23	1.26		0.15	2.03	**	-0.05	-2.39	**
Style	Y			Y			Y			Y		
Firm	Y			Y			Y			Y		
Year	Y			Y			Y			Y		
Num. of Obs.	67,176			66,803			66,803			65,199		
Adj. R^2	6.31%			6.62%			6.27%			5.53%		