Hedge Funds and ESG Sentiment

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Abstract

This paper investigates whether hedge funds can capitalize on fluctuations in ESG sentiment. Using a novel dataset capturing worldwide public perceptions of ESG discussions, I construct composite and pillar-level ESG sentiment indices. I find hedge funds actively time ESG sentiment by anticipating future sentiment shifts and exploiting short-term lags between sentiment changes and subsequent stock price adjustments to generate higher alpha and reduce downside risks. Funds' timing skills vary across strategies, with directional and semi-directional funds exhibiting stronger average timing abilities. These results highlight that hedge funds can harness public, values-based perceptions of ESG practices for performance and risk management.

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"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 rising attention to ESG-related discussions within financial markets. Beyond public attention, ESG sentiment has been shown to influence asset prices and hedge risks (de Franco, 2020; Engle et al., 2020; Serafeim, 2020; Pastor et al., 2021; Ardia et al., 2023). Hedge funds, as sophisticated market participants, actively leverage high-ESG stock-picking skills and factor exposures to enhance performance and manage risks (Liang et al., 2022; Aragon et al., 2024; Kuang et al., 2024). Prior studies also document their superior market-timing abilities in profitability-driven conditions (Chen and Liang, 2007; Cao et al., 2013; Chen et al., 2021). This naturally leads to the question: can hedge funds strategically time ESG sentiment—a values-based market signal—to generate alpha and reduce risks? This paper investigates their proactive timing skills across environmental, social, and governance (ESG) pillars.

Specifically, I 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, I use the LSEG MarketPsych ESG Analytics dataset, which measures firm-level ESG sentiment from news and social media in near real time using

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

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), I 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.

I 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, I explore the mechanism underlying these timing strategies. Specifically, I investigate how hedge funds adjust their stock holdings in response to changes in pillar-level sentiment. I 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, I 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, I 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.

My 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., 2018; Grinblatt et al., 2020). I 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. 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. My 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, I contribute to the construction of ESG sentiment indices. Prior work focuses 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. I 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 reviews the related literature. Section 3 describes the data and presents descriptive statistics. Section 4 outlines the construction of ESG sentiment indices. Section 5 measures hedge funds' pillar-level timing skills and examines their implications for performance and risk mitigation. Section 6 investigates the mechanisms underlying hedge funds' proactive pillar timing and the drivers of superior performance. Section 7 presents robustness checks, and Section 8 concludes.

2. Literature Review

2.1 Hedge Fund Skills

Hedge funds, as sophisticated arbitrageurs, exploit market inefficiencies through superior stock-picking and market-timing skills. Compared with mutual funds, hedge funds exhibit stronger stock-selection ability (Griffin and Xu, 2009), often holding undervalued stocks and correcting market mispricing (Cao et al., 2018a, 2018b). Contrarian hedge fund managers, in particular, demonstrate persistent and profitable stock-picking skill (Grinblatt et al., 2020). Moreover, timing skill is particularly important: Chen and Liang (2007) and Cao et al. (2013) document that hedge funds with superior market-timing abilities achieve higher performance and better execution of trading strategies. More recently, Chen et al. (2021,

2024) show that hedge funds can strategically time investor sentiment, profiting from sentiment-driven price movements by entering early and exiting before noise traders. These findings suggest that hedge funds may similarly possess the skill to strategically respond to market-level ESG sentiment, rather than passively following trends.

2.2 Institutional Investors and Sustainable Investment

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). Hedge funds' ESG investments are debated: historically favoring brown stocks pre-2011 (Avramov et al., 2022), yet socially responsible funds attract more flows, assets, and revenues (Liang et al., 2022). High green-beta funds outperform with lower risk (Kuang et al., 2024), and UNPRI adoption improves flows and asset accumulation (Liang et al., 2022). Early ESG integration enhances future risk-adjusted returns without social tilts (Pancholi, 2022), and active shorting of brown firms incentivizes green innovation (Liang et al., 2024). However, it remains unclear whether public sustainability sentiment influences hedge fund exposures, performance, and risk, or whether funds can time this sentiment. The drivers of hedge funds' ESG sentiment trading strategies also remain underexplored.

2.3 Investor and Public Sentiments

Investor sentiment (“Animal Spirits”; Keynes, 1936) significantly affects asset prices and stock returns (DeLong et al., 1990a, 1990b; Baker and Wurgler, 2006, 2007), with mispricing intensifying during high-sentiment periods (Stambaugh et al., 2012). Measurement approaches have evolved from market indicators to sophisticated unstructured data analysis. Unstructured data—including news, social media, conference calls, and textual analysis—effectively captures sentiment dynamics, consistently predicting asset returns and market movements (Tetlock, 2007; Da et al., 2011; Garcia, 2013; Calomiris and Mamaysky, 2019; Kraussl and Mirgorodskaya, 2014; Dang et al., 2015; Binsbergen et al., 2023; Garcia et al., 2023; Bybee et al., 2024; Obaid and Pukthuanthong, 2022). Executive and individual sentiment also influence markets (Goetzmann et al., 2024). Hedge funds, as sophisticated arbitrageurs, exploit these signals by strategically timing positions, entering early and exiting before noise traders (Brunnermeier and Nagel, 2004; Chen et al., 2021). Within sustainability investing, ESG sentiment shapes institutional positions, portfolio profits, and corporate outcomes (Serafeim, 2020; Ardia et al., 2022; Ilhan et al., 2023; Leung et al., 2023; Li et al., 2024; Arthur et al., 2025; Aggarwal et al., 2024). Flow-driven ESG dynamics further amplify these effects (van der Beck, 2024). Since hedge funds typically employ top-down strategies responding to macro-level sentiment signals (Smith et al., 2016; DeVault et al., 2019; Chen et al., 2021), a market-level aggregation approach better captures their sentiment trading behavior. Accordingly, I construct a composite market-level ESG sentiment index from global news and social media to reflect aggregate public perceptions for firms’ ESG practices.

3. Data

3.1 Public Sustainability Sentiment

This study relies on two primary data sources. The first is the LSEG MarketPsych ESG Analytics database, which offers public sentiment data on sustainability. The database uses advanced natural language processing (NLP) techniques to analyze unstructured news and social media data from over 300,000 sources in 13 languages.[2] It offers more than 100 metrics for granular ESG assessments, encompassing both pecuniary and non-pecuniary issues, such as global business news, social media, watchdog groups, ESG-focused news providers, environmental NGOs, and social monitors (Aggarwal et al., 2024). Key features of the database include real-time sentiment analysis across various time windows (60 seconds, hourly, daily), source-specific tone analytics, verified entity identification, and advanced linguistic flow analysis.[3]

The database provides 23 directional scores ranging from -1 to 1, capturing net sentiment across various ESG dimensions, including emissions, environmental innovations, resource use, community, human rights, product, workforce, management, and shareholders. For this study, I use these 23 variables (7 in the Environmental, 11 in the Social, and 5 in the

[2] One key advantage of the LSEG Marketpsych database is its inclusion of social media sources, which sets it apart from previous literature that primarily relies on databases like RavenPack (Dang, Moshirian, and Zhang, 2015) and TruValue Lab (Serafeim, 2020; Leung et al., 2023; Li, Watts, and Zhu, 2024; Zhou, 2024). This inclusion offers a more comprehensive view of public sentiment regarding firms' ESG practices.

[3] The LSEG MarketPsych database employs advanced NLP metrics with tone-level analytics for both news and social media. For instance, a phrase like "Management crushed it!" may be correctly identified as positive toward a firm, whereas traditional NLP might misclassify it as negative. The database also addresses challenges such as company aliases and spelling variations through manual review, while weighting adjectives, verb tenses (past, present, future, conditional), and intensity to capture nuance. To reduce greenwashing risk, company-generated content is excluded from sentiment calculations; for example, news quotes from company spokespeople are removed to avoid bias in ESG assessments.

Governance pillars) as public sentiment indicators.[4] The database includes data for 93,378 companies from 173 countries with at least one non-empty ESG sentiment variable.

An example of sentiment score calculation is the determination of the Product Sentiment score. This score is derived by calculating weighted scores for positive and negative statements about a company's products, normalized by the total number of mentions (Buzz). For example, a sentence such as "*Company X has developed sustainable products*" contributes positively, while "*Company X's products were harmful to the environment*" contributes negatively. The Product Sentiment score for a company is calculated as (Positive score - Negative score) / Buzz (Buzz is 2 in this case).

[Insert Figure 1]

Figures 1A, 1B, and 1C show the mean sentiment values for firms worldwide, with European, Asia-Pacific, and Australian firms generally exhibiting higher ESG sentiment across all three pillars. Specific countries with the highest sentiment for each pillar include France, Norway, and Italy for Environmental sentiment; India, Japan, and Pakistan for Social sentiment; and Australia, Malaysia, and Canada for Governance sentiment.[5]

[4] Regarding sentiment variables, my paper differs from Aggarwal et al. (2024), who use industry-adjusted weighted scores for the E, S, and G pillars to analyze relative sentiment across firms within the same industry and its relation to shareholder actions. In contrast, I use individual sentiment variables to capture overall market-level/public ESG sentiment, which is more appropriate for hedge funds that invest across multiple industries. Although the database offers over 100 metrics, I focus on 23 variables to measure public net ESG sentiment. According to LSEG, the controversy metrics (negative sentiment and most unused variables) are included as a subset of the net sentiment scores.

[5] France's top Environmental sentiment likely reflects its leadership during the COP21 presidency, which fostered global trust and collaboration and led to the swift ratification of the Paris Agreement. India leads in the Social pillar due to its 2013 mandate making CSR obligations compulsory for firms. Australia ranks highest in

LSEG MarketPsych provides real-time sentiment across various time windows. For this study, I use daily firm-level ESG sentiment data, aggregated monthly (mean) to match the hedge fund database used in the analysis (TASS, discussed in the next section). This results in a time-series dataset of monthly averages from January 2003 to December 2024.

The ESG sentiment variables in this paper are sourced from both news vendors and social media platforms, influencing public perceptions of companies. These monthly-aggregated ESG sentiment variables capture public and market-level sentiments across the three pillars, with 23 detailed metrics, provided in a time-series format.

[Insert Table 1]

Panel A of Table 1 presents summary statistics for the monthly-aggregated ESG variables. The Environmental pillar has the highest average sentiment (0.12) and the largest standard deviation (0.08), driven primarily by *Sustainability Improvement* and *Airborne Emissions Improvement*. The Social pillar has the second-highest mean sentiment (0.10), with the lowest standard deviation (0.05), largely influenced by *Access Affordability*. The Governance pillar has the lowest mean sentiment (-0.01) and the second-highest standard deviation (0.07), mainly driven by *Shareholders*.

3.2 TASS

The second data source in this paper is TASS, which provides information on hedge

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Governance, driven by its 2019 whistleblower protection law, which set a precedent for corporate accountability.

fund performance, characteristics, asset instruments, and focus details from January 2012 to December 2024. I 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, I have 4,557 funds from 1,591 unique firms.[6] Descriptive statistics for the funds' performance and characteristics are presented in Panel B of Table 1.

Table 2 in Appendix presents the investment approaches, asset allocations, and investment focuses for funds. The table shows that on average, most funds allocate more to equities, futures (fixed income), commodities, and currency forward contracts. Additionally, most funds prefer bottom-up and fundamental investment approaches. Geographically, most funds focus on global investments, with a strong emphasis on Latin America and the USA, as well as a moderate focus on Western Europe (primarily the UK) and the Asia Pacific region.

3.3 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:[7]

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[6] 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.

[7] $Excess\ Return_t$ 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), I test hedge fund exposures to the relevant ESG sentiment variables using a return-based methodology. The excess return is calculated by subtracting the 3-month US Treasury Bill return from the monthly rate of return. Additionally, I use the changes in sentiment as the main independent variable, as done by Chen et al. (2021).

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

For each fund i at month t, I 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.[8] Y_i and S_i represent the total number of years and styles for fund i.[9] 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 among hedge funds. This may be attributed to the role of Corporate Social Responsibility (CSR)

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

[9] 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 5.2.

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.

3.4 Hedge Fund Stock Holding Positions

I obtain hedge fund managers' stock holding positions from the LSEG Institutional Holdings (Form 13F) database, which reports quarterly changes in institutional equity holdings. I 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.

4. Public ESG Sentiment Index

4.1 Composite and Pillar-wise ESG Sentiment Index

In this section, I construct a uni-dimensional public ESG sentiment index using Principal Component Analysis (PCA).[10] Following the methodology of Baker and Wurgler (2006, 2007), I use the first principal component (PC) as the composite ESG sentiment index. As shown in Figure 2, the first principal component accounts for 53.76% of the variance, indicating that it captures the majority trajectories among ESG sentiment variables. This approach allows for a more concise and effective measure of overall ESG sentiment, reducing multicollinearity and preserving the essential information.

[Insert Figure 2]

Table 3 presents the loadings of the variables, rank summary statistics, and the results of the relative importance tests for the median rank across the three pillars. The rank is based on the magnitude of the loadings for each variable. Among the top 11 variables, 6 are from the environmental pillar (note that there are only 7 variables in the E pillar in total). *Airborne Emission Improvements* and *Sustainability Improvements* are identified as the two most

[10] Eskildsen et al. (2024) calculate the average of the 23 green measures from five rating agencies to construct an aggregate score. In contrast, my study addresses a different concern—namely, the high correlations among the ESG sentiment variables—rather than the potential confusion stemming from variations between rating agencies. To mitigate multicollinearity and retain the maximum variance within the data, I employ Principal Component Analysis (PCA) as an unsupervised learning method to construct the uni-dimensional ESG sentiment index. This approach effectively captures the primary variation across the 23 sentiment variables while minimizing the issues associated with collinearity.

important variables, which are consistent with the ranking of the hedge fund excess return exposures within the environmental pillar (Panel A of Table 2).

Additionally, variables like *Workplace Sentiment* and *Trust* remain the top two important social variables, consistent with Table 2, emphasizing the crucial role of maintaining CSR bonds between employers and employees, as well as between companies and their customers. In the governance pillar, *Accounting Sentiments*, which measure perceptions of accounting practices, maintain the same rank (5th) in both Table 3 and the hedge fund excess return exposures in Table 2. Shareholders emerge as the most important variable, according to the maximum variance, among all 23 variables. This finding aligns with Aggarwal et al. (2024), who argue that negative sentiment towards financial, environmental, and social issues leads to increasing dissatisfaction among investors.[11]

[Insert Table 3]

Panels B and C of Table 3 present the median rank tests for the three pillars. Consistent with the excess return exposure results in Table 2, the environmental pillar is relatively more important than the social pillar, and the social pillar is more important than the Governance pillar. Additionally, 6 variables from the top 11 of the first principal component (PC) loadings in Panel A of Table 3—*Airborne Emissions Improvement*, *Sustainability Improvement*,

[11] Note that according to Panel A of Table 1, the mean and median of the *Shareholders* are all negative.

Pollution Improvement, *Accounting Sentiment*, *Workplace Sentiment*, *Trust*, and *Climate Policy*—also remain among the top 11 for excess return exposure magnitude.

These results suggest that hedge funds not only actively respond to ESG sentiment changes, but more importantly, they demonstrate potential skill in identifying and timing exposure to dominant ESG sentiment variables. Specifically, the hedge fund exhibits the stronger return sensitivity to those ESG sentiment variables that define the primary dimension of ESG sentiment variation (as measured by first principal component loadings). This systematic alignment between factor importance and return predictability indicates sophisticated ESG signal processing capabilities and systematic sentiment timing rather than broad or indiscriminate ESG exposure.

Using the loadings of the variables presented in Table 3, I construct a unidimensional ESG sentiment index.[12] Figure 3 shows the monthly-level composite ESG sentiment index from 2003 to the end of 2024. The trajectory of the index captures major improvements and scandals related to global ESG regulations and pillar-related events. The peaks represent key ESG policy developments, such as the UN Sustainable Development Goals framework in 2012, the ESG Disclosure Simplification Act in 2021, and the adoption of the European Sustainability Reporting Standards in 2023. Notable environmental milestones include the EPA Ozone Standard implementation in 2004 and the release of the IPCC Fourth Assessment Report in 2007 (Intergovernmental Panel on Climate Change, 2007). The index also captures major

[12] In untabulated results, I also construct region-level ESG sentiment indices using the same methodology, with EU countries, the UK, and South Asia exhibiting rising ESG sentiment trends over time.

corporate scandals including environmental incidents (Ivory Coast toxic waste dump, 2006), greenwashing concerns, governance failures (Occidental Petroleum v. Ecuador scandal in 2004), and data privacy breaches (Facebook-Cambridge Analytica scandal 2019) that significantly influenced public ESG sentiment during this period.

[Insert Figure 3]

In addition to the composite index, I also construct pillar-wise indices using the weights derived from the loadings of the first PC.[13] Figure 4A presents the three pillar indices at the monthly level.[14] A key insight from the figure is that the three pillars exhibit different trajectories across the years. This suggests that, in addition to the need for a composite sentiment index, the pillar-wise indices are also valuable for a more nuanced 'decomposition' analysis.

[Insert Figure 4]

[13] For the pillar indices, I continue to use the first principal component (PC) loadings as fixed weights, but I apply them specifically to the variables corresponding to each respective pillar.

[14] The 'peaks' in the governance pillar during the 2007–2008 financial crisis may initially appear counterintuitive. However, it is important to note that governance sentiment remained negative from the onset of the recession until the third quarter of 2008. The first peak corresponds to the implementation of the Troubled Asset Relief Program (TARP) in October 2008 (https://home.treasury.gov/data/troubled-asset-relief-program). The second peak, occurring near the end of the recession, reflects a sentiment value slightly above zero, suggesting a modest recovery in governance sentiment as market conditions began to stabilize.

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

5.1 Hedge Fund Pillar Exposures and Timing Skills

In this section, I measure hedge funds' pillar-level exposures and timing skills. The estimation approach is presented in Equation 2.

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

X denotes the environmental, social, and governance pillars. $\Delta Sentiment_t^X$ represents the monthly change in pillar-level sentiment, calculated as $Sentiment_t^X - Sentiment_{t-1}^X$. Following Chen et al. (2021), β_{it}^{XSE} a fund's exposure—its return sensitivity—to changes in pillar-level sentiment. $\gamma_{it}^{XST;\,CCLL}$ measures pillar sentiment timing ability, conditional on market factors, following the approach of Cao et al. (2013). Specifically, it reflects how funds adjust their exposures in response to detrended changes in pillar sentiment. 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. A larger β_{it}^{XSE} implies that fund i has greater exposure to changes in pillar sentiment, while a larger $\gamma_{it}^{XST;\,CCLL}$ indicates stronger timing ability at time t. In later sections, I also introduce alternative timing approaches for robustness. f_t represents the nine hedge fund factors identified by Chen et al. (2025). All models include fund style and year fixed effects, with standard errors clustered at the fund style and year levels.

5.2 Pillar Exposures and Timing Skills Predicting Performance

This section examines whether hedge funds' pillar-level timing skills predict future outperformance. Panel A of Table 4 reports the predictions for alpha, Sharpe ratio, appraisal ratio, and Sortino ratio using Equation 3.[15]

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

$\hat{\beta}_{it-1}^{XSE}$ and $\hat{\gamma}_{it-1}^{XST}$ are the pillar-level exposures and timing skills from Equation (2) in Section 5.1. $\hat{\gamma}_{it-1}^{Investor}$ captures fund i's investor sentiment timing skill in month t by adopting Cao et al. (2013)'s method. τ_X measures whether a fund with both higher exposure and

[15] 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.

stronger timing skill for pillar X achieves higher alpha ($CLTZ\ HF9\ Alpha_{it}$)[16] or risk-adjusted returns in the subsequent month.

Panel A of Table 4 shows that funds with superior exposure and timing in the previous month generate additional alpha of 2%, 3%, and 1% for the environmental, social, and governance pillars, respectively. Models 2–4 demonstrate that these benefits extend to general (Sharpe ratio), idiosyncratic (appraisal ratio), and downside risk-adjusted returns, indicating that higher timing skill combined with greater exposure leads to superior risk-adjusted performance.

[Insert Table 4]

Comparing across pillars, the main performance benefits stem from the environmental and social pillars. Social pillar timing delivers relatively higher short-term performance (larger coefficients), while environmental pillar timing yields more sustained performance growth (more statistically significant). The social pillar's acute impact reflects rapid market reactions to events such as *Customer Satisfaction*, *Workplace Sentiment*, and *Trust*. By contrast, environmental pillar effects are driven by ongoing public discussions of firms' practices and emerging environmental policies, producing a longer-term, persistent impact on equity and asset prices.

[16] $CLTZ\ HF9\ Alpha_{it}$ is the Chen et al. (2025) 9 factor alpha that is calculated by $Excess\ Return_t = \alpha_t + \theta' f_t + \varepsilon_t$.

5.3 Pillar Exposures and Timing Skills Predicting Risks

A key finding from Section 5.2 is that funds with higher pillar exposures and timing skills achieve better Sortino ratios, suggesting potential benefits for downside risk management. To examine this, we estimate the following risk prediction model (Equation 4):

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

$Stdev$ measures total fund risk (36-month rolling standard deviation), while $Tail\ risk$ and $Expected\ shortfalls$ capture downside risk (left 5% tail of monthly returns). The focus is on whether $\tau_X > 0$ indicates that higher exposure and stronger timing skill in the previous month help mitigate risk.

Panel B of Table 4 shows that the primary risk-reducing benefits come from the environmental and social pillars. Higher exposure and timing skills in these pillars reduce total risk by at least 3% and decrease downside risk measures (tail risk and expected shortfall) by at least 4%, demonstrating that superior pillar timing not only enhances returns but also contributes to effective risk management.

5.4 Dissecting Downside Risk Mitigation Outcomes

To understand what drives the total and downside risk mitigation benefits for funds with superior timing skills, we apply an alternative measure of pillar exposures and timing skills that emphasizes downside risk management. Specifically, we use the Henriksson and Merton (1981, HM) approach with daily pillar sentiment adjustments from Goetzmann et al. (2000, GII). The model is:

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

$\beta_{it}^{XSE;HM\&GII}$ measures pillar exposures: higher values indicate increased fund exposure when pillar sentiment rises above its 36-month average. $\gamma_{it}^{XST;\,HM\&GII}$ captures the fund's adjustment of exposures downward when sentiment changes are below average. This approach captures dynamic timing strategies and reflects hedge funds' downside risk management philosophy, particularly for ESG investments.

Panel A of Table 5 presents 5×5 portfolio sorts of funds by HM&GII pillar exposures ($\beta_{it}^{XSE;HM\&GII}$) and timing skills ($\gamma_{it}^{XST;\,HM\&GII}$). Cells show average monthly alpha for each quintile group. The top-minus-bottom spreads (rightmost columns and bottom rows) indicate that higher exposures combined with superior timing skills yield monotonically increasing alpha, with the largest benefits in the environmental (16 bps) and social (25 bps) pillars. Panel B, using the Cao et al. (2013) method and Chen et al. (2021) exposures, shows similar monotonic improvements.

[Insert Table 5]

Note that both panels' sorting results are based on funds with statistically significant exposures and timing skills. The rightmost Top-Bottom columns show that higher pillar exposures combined with superior timing skills lead to monotonically increasing alpha. A natural question is whether funds with higher exposures also have stronger timing skills. Table 6 shows that across the three pillars, over 36% of funds have significant exposures, and among these, more than 65% exhibit significant timing skills. These results suggest that higher pillar exposures generally coincide with superior timing skills, delivering enhanced fund performance.

[Insert Table 6]

5.5 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, I 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.

6. Hedge Fund Timing Skill Mechanism

Beyond the outcomes documented in Section 5, understanding the mechanism behind hedge funds' pillar timing skills is crucial. Specifically, I 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]

7. 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 the determinants of engagement in ESG sentiment trading. I first assess whether funds with higher prior timing skills deliver persistent performance. Figures 6A and 6B present predictions for 9-factor alpha and Sortino ratios using 1 to 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 the results in Section 5, 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 suggest that superior pillar timing skills not only enhance next month's performance but also contribute to persistent alpha and downside-risk-adjusted returns.

[Insert Figure 6]

Next, I 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]

I then explore 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, using the model presented in Equation 6.

$$Flow_{it} = \alpha_{it} + \sum_{X\in\{E,S,G\}}[\delta_{HTT}^{X}\, High\ Trank_{t-1} \times \hat{\gamma}_{it-1}^{XST} + \delta_{MTT}^{X} Mid\ Trank_{t-1} \times \hat{\gamma}_{it-1}^{XST} + \delta_{LTT}^{X} Low\ Trank_{t-1} \times \hat{\gamma}_{it-1}^{XST} + \delta_{XST}\hat{\gamma}_{it-1}^{XST}] + \delta_{Investor}\hat{\gamma}_{it-1}^{Investor} + \delta_{HT} High\ Trank_{t-1} + \delta_{MT} Mid\ Trank_{t-1} + \delta_{LT} Low\ Trank_{t-1} + \delta_{M} Management\ Fee_{t-1} + CFlow_{t-1}^{\prime\delta_{CFlow}} + \sum_{j=1}^{14}\rho_j StyleDummies_j + \sum_{q=1}^{11}\eta_q YearDummies_{qi} + \sum_{f=1}^{1487}\varphi_f FirmDummies_{qi} + \varepsilon_{it} \tag{6}$$

The results indicate that the largest inflow benefits occur for funds with high past returns, but importantly, even mid- and low-performing funds experience positive flows, though the magnitudes decrease monotonically across terciles. Across all three pillars, mid- and low-tier funds maintain positive fund flow effects, highlighting the broader appeal of superior timing skills.

[Insert Table 8]

Finally, I investigate the determinants of hedge funds' engagement in ESG sentiment trading. Using fund-level characteristics related to asset allocation, investment focus, investment approach, and geographic focus, I predict next-month ESG sentiment beta via LASSO regression. The fund-level predictions are estimated using LASSO regression, as outlined in Equation 7.[17]

$$\min_{\beta_j} \sum_{i=1}^{n} \left(\hat{\beta}_t^{ESGS} - \sum_{j=1}^{p} \boldsymbol{X}_{\boldsymbol{AFI\ t-1,j}} \boldsymbol{\beta}_{\boldsymbol{AFI\ t-1,j}} \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \tag{7}$$

The top predictors reveal distinct patterns across pillars: environmental pillar timing skills are stronger for funds investing in resource-intensive sectors (e.g., *Softs*, *Base Metals*, *Biotechnology*, *Shipping*) or environmental/resource-focused geographies (*Western Europe*, *Russia*); social pillar 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 pillar timing skills are elevated for funds focusing on traditional corporate securities, bonds, or corporate-event-driven strategies (e.g., *Bankruptcy*) where management quality directly impacts valuations. Collectively, these results demonstrate that hedge funds' ESG pillar timing skills are persistent, measurable across methodologies,

[17] I 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, I 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. I then regress the fund-level average ESG sentiment beta on these averaged characteristics.

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).

rewarded by fund inflows, and systematically linked to their investment orientation and focus.

[Insert Table 9]

A further question arises: How do my ESG sentiment and pillar indices compare to related benchmark indices? To address this, I use the topic attention indices developed by Bybee et al. (2024) [BKMX] as benchmarks for my pillar indices.[18] For each pillar, I select two indices that are most relevant to the pillar categories. For the E pillar, I use the 'Environment' and 'Natural Disasters' indices; for the S pillar, I use 'Diseases' and 'Gender Issues'; and for the G pillar, I use 'Bankruptcy' and 'Corrections/amplifications.' Additionally, further control the two climate change sentiment indices from Engle et al (2020) [EGLKS] and Ardia et al. (2023) [ABBI] for further robustness tests. Figure 2 in Appendix shows comparisons of my constructed pillar indices with corresponding topic indices. The times when these topic indices receive significant attention also correspond to major peaks and troughs in sentiment.[19]

Table 3 in Appendix presents a pillar-wise 'horse race' comparison between my significant pillar sentiment timing skills, as well as the three other indices (BKMX, EGLKS, and

[18] Bybee et al. (2024) uses topic modeling approach captures the attentions of sentimental-related, appraisal, and appraisal-free topics. The range of their data is from January 1985 to December 2017.

[19] The correlations between my E sentiment index and Environment and Natural Disasters are 0.16 and -0.45, respectively. The correlations between my S sentiment index and Disease and Gender Issues indices are 0.19 and 0.45, respectively. The correlations between my G sentiment index and Bankruptcy and Corrections/amplifications are -0.21 and -0.16, respectively.

ABBI), evaluating Sortino ratio, appraisal ratio, CLTZ HF9 alpha, standard deviation, tail risks, 95% expected shortfalls, and fund flow predictions. Panels A, B, and C provide robustness tests for each pillar, controlling for the related topic indices (at $t-1$). When the previous indices are linked to negative sentiment-related topics (e.g., Disasters, Diseases, Bankruptcy, and Corrections/amplifications), there is a negative correlation between hedge fund future performance and fund flows, and a positive correlation with future risks. Conversely, for topics related to positive or neutral sentiment, such as Environment, the correlations are reversed. Additionally, when controlling the topic indices, my three-pillar sentiment timing skills remain significant predictors of outperformance, increased inflows, and lower total and downside risks at the 5% level.

According to this section, hedge funds' ESG pillar timing skills are persistent, measurable across methods, and economically meaningful, driving sustained performance, downside risk mitigation, and positive fund flows, with their effectiveness shaped by investment focus, strategy, and sectoral/geographic orientation.

8. Conclusion

this paper demonstrates that hedge funds can effectively time values-based market-level ESG sentiment to generate performance and risk management benefits. Using high-frequency, firm-level ESG sentiment data aggregated into composite and pillar-level indices, I show that funds—particularly those with directional or semi-directional strategies—exhibit significant exposures and proactive timing abilities, especially along the environmental and social pillars. Superior ESG timing skills are associated with persistent alpha, improved downside-risk-adjusted returns, and increased fund inflows, even among mid- and low-performing funds, highlighting the economic value investors place on such skills. Mechanistically, hedge funds anticipate shifts in pillar-level sentiment, increasing long positions ahead of sentiment surges and capitalizing on the delayed market reactions to public ESG perceptions. Furthermore, fund characteristics, including sectoral focus, geographic allocation, and investment approach, systematically predict ESG timing abilities, suggesting that expertise and resources play a critical role in exploiting ESG signals. Overall, this study extends the literature on hedge fund skill measurement, institutional ESG engagement, and sentiment-based asset pricing by identifying ESG pillar timing as a novel, forward-looking skill that contributes to both alpha generation and risk mitigation in financial markets.

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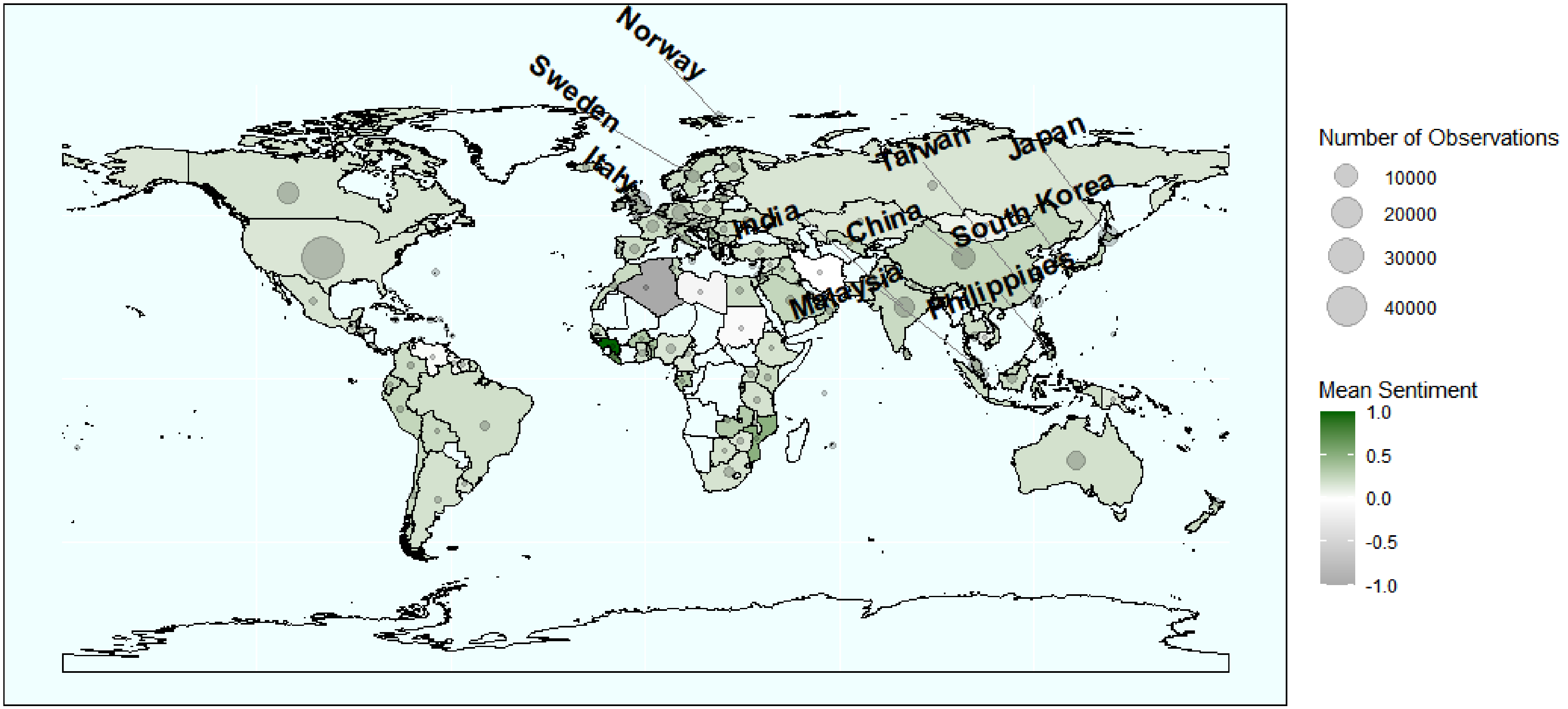
Figure 1 Country-level ESG Sentiment

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.[22] 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



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

Figure 1B Social Pillar Sentiment

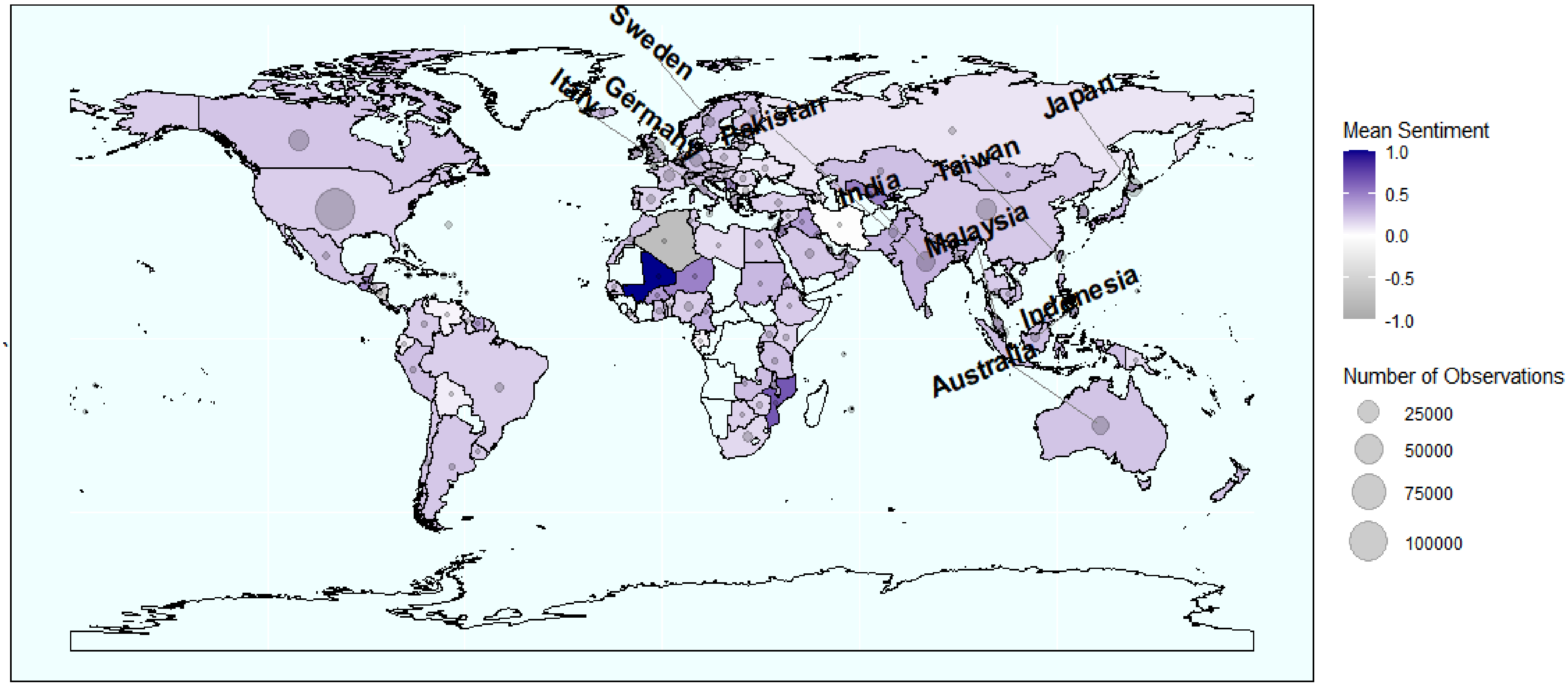


Figure 1C Governance Pillar Sentiment

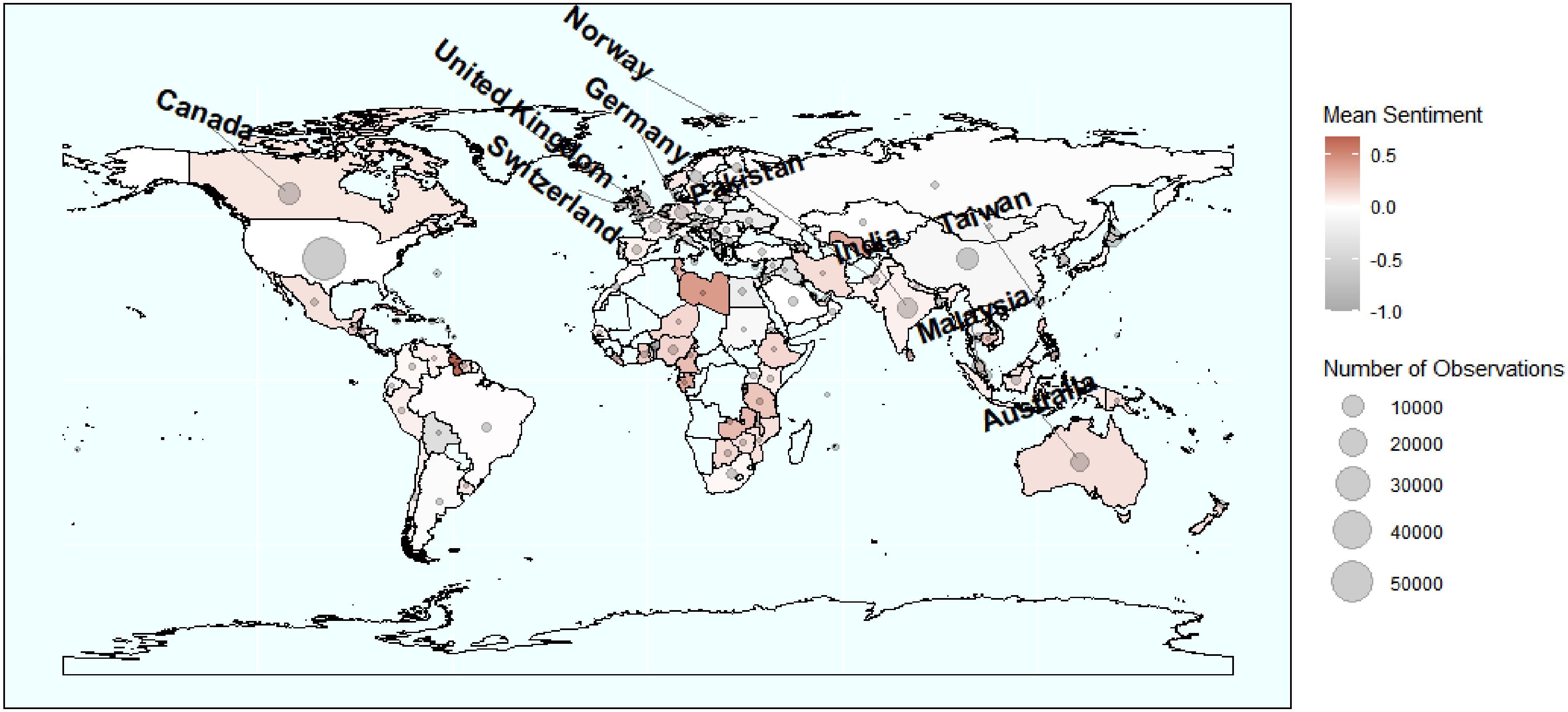
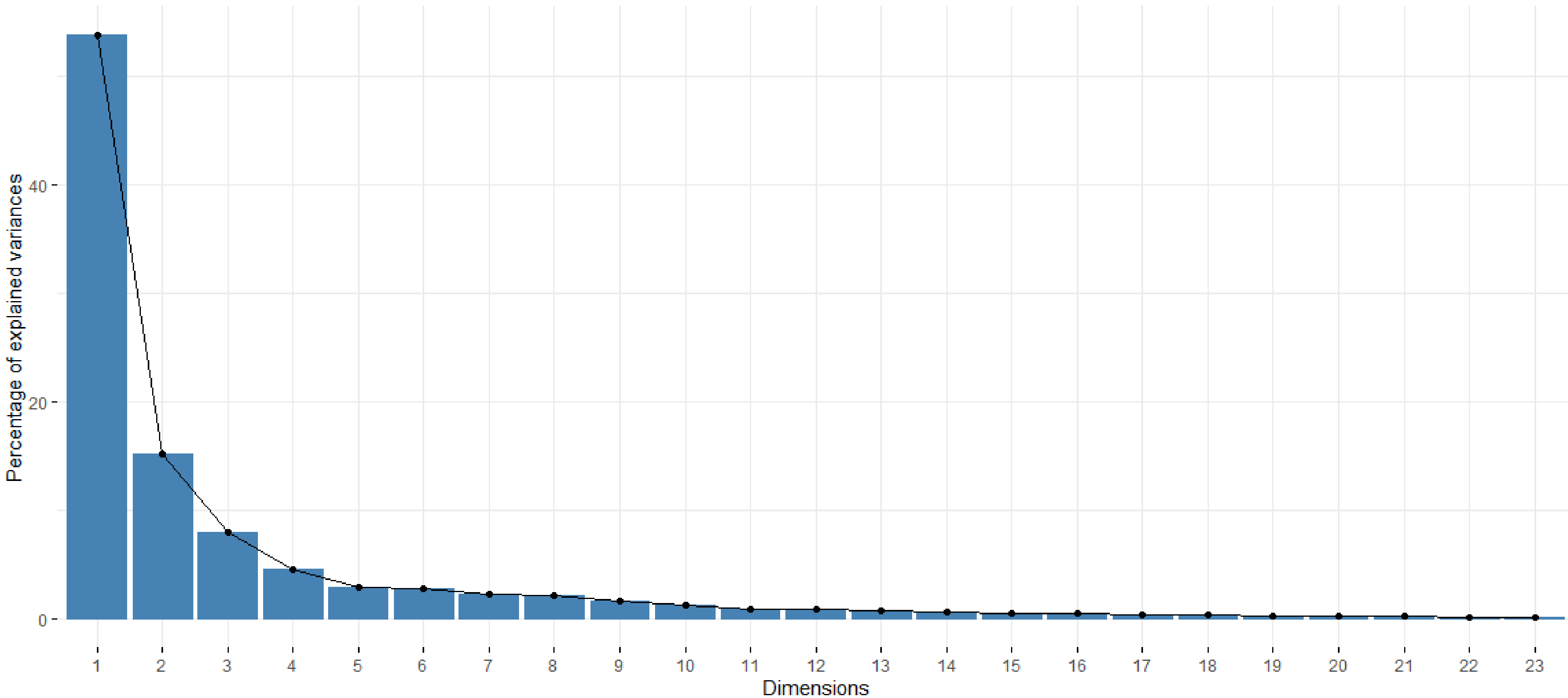


Figure 2 PCA Explained Variance Plot for ESG Sentiment Variables

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.[23]

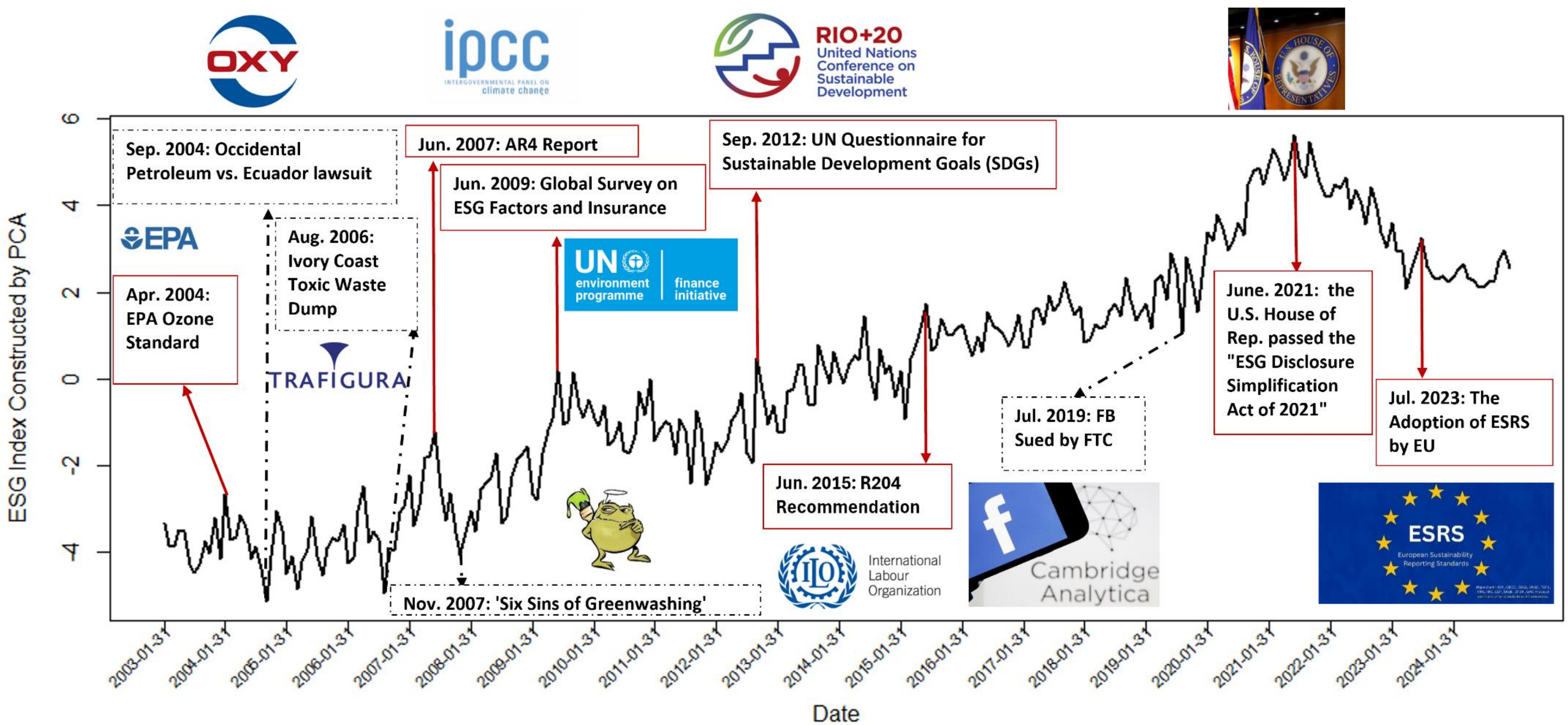


[23] The original net sentiment variables are on firm-level, I aggregate to the monthly level by taking the average of each variable within the respective month. The net sentiment variables range from -1 to 1, include 7 environmental, 11 social, and 5 governance variables.

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.[24] 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



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24 The original net sentiment variables are on firm-level, I 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

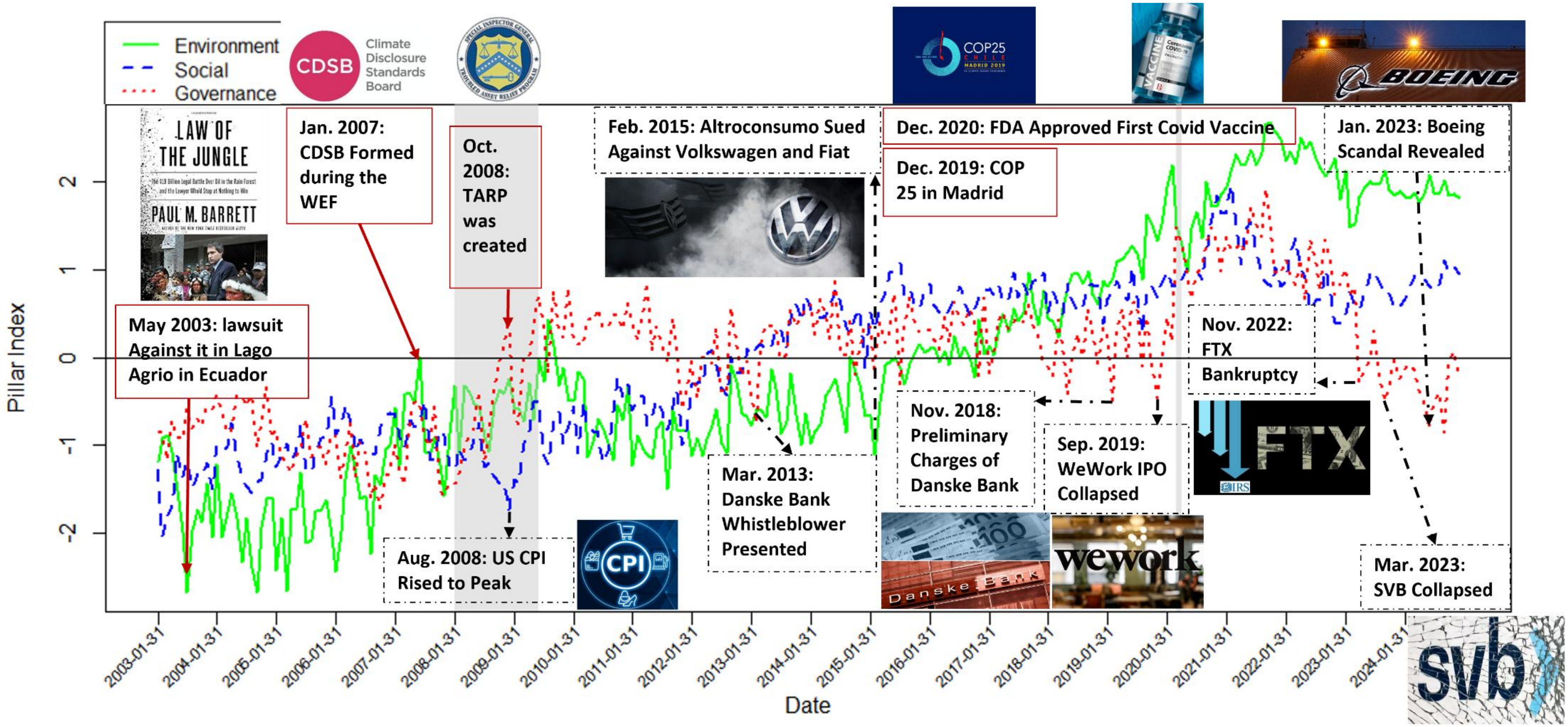


Figure 4 Hedge Fund Long-Only Share Changes Around Above-Average ESG and Pillar Sentiment Changes

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.

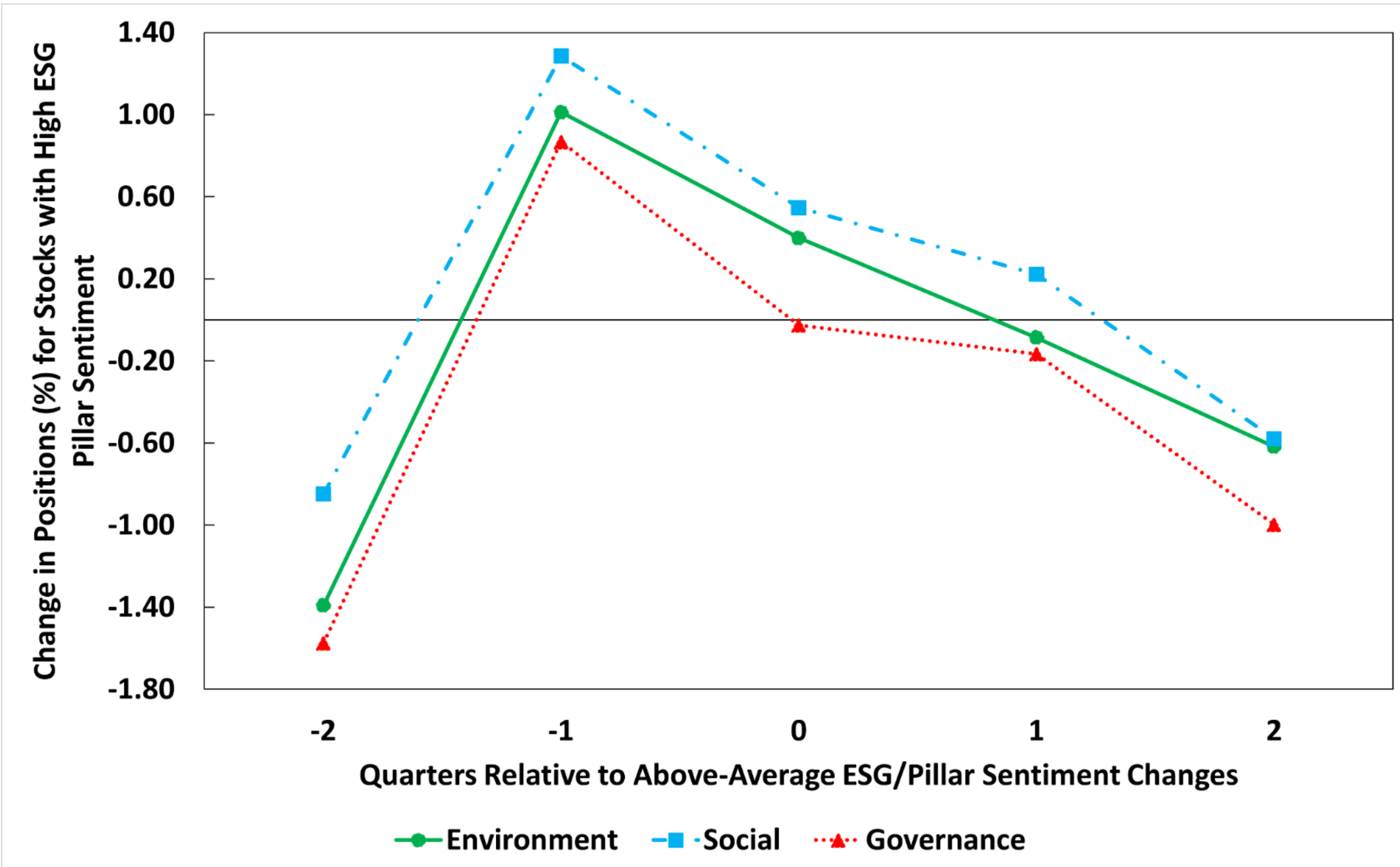


Figure 5 ESG Sentiment Changes Event Study

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.

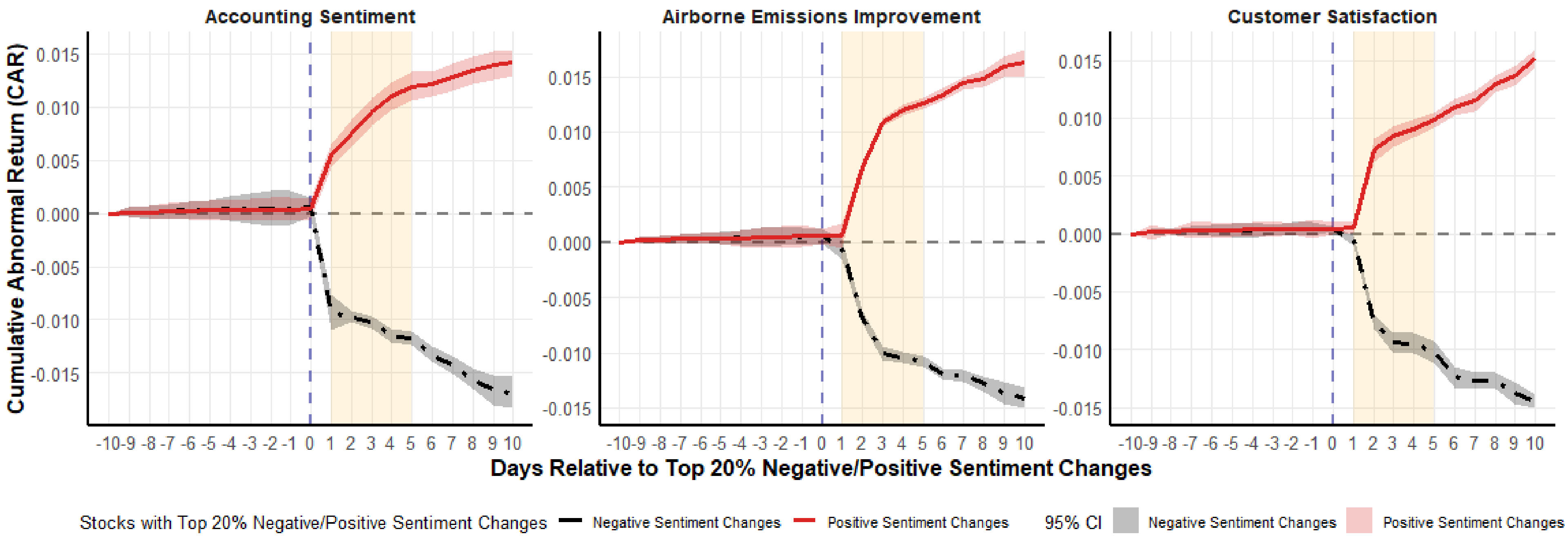


Figure 6 Persistence of ESG Sentiment Timing Skills in Predicting Alphas and Sortino Ratios

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.[25] 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

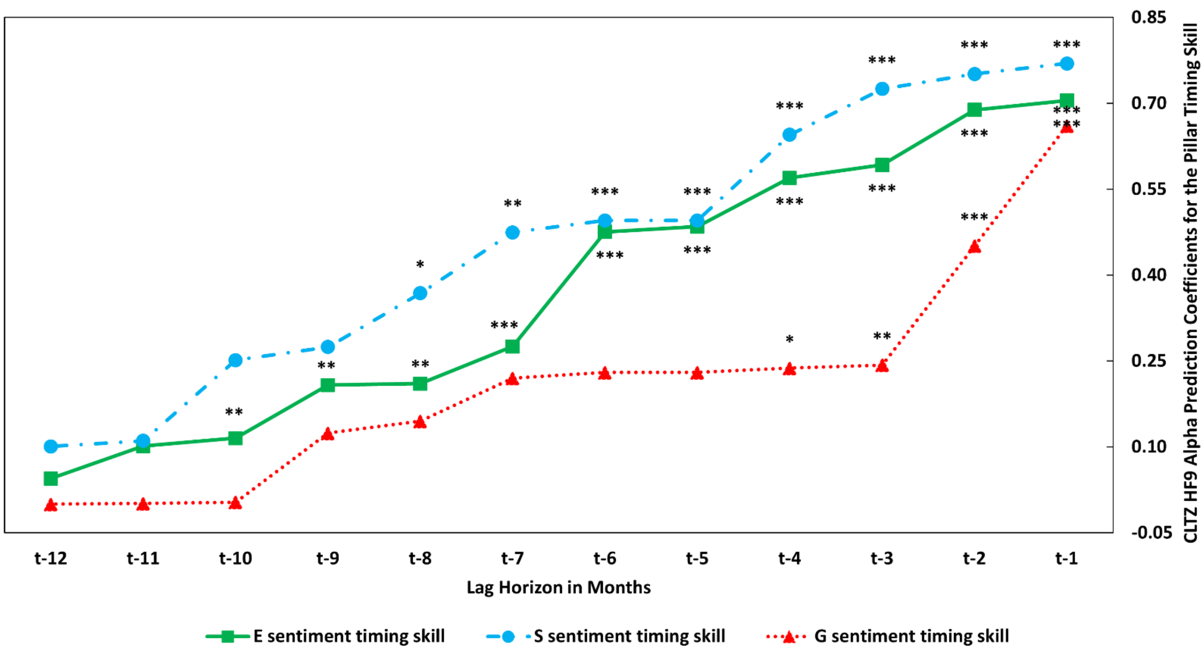
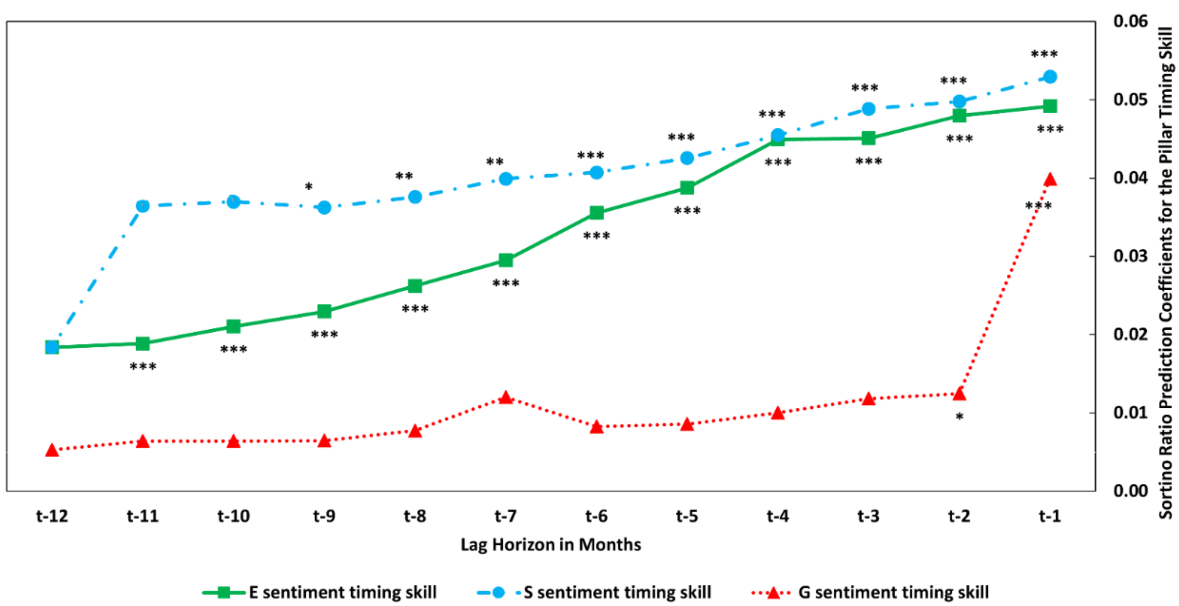


Figure 6B Persistence of ESG Sentiment Timing Skills in Predicting Sortino Ratios



[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. 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.[26] The observations in Panel B are presented at the fund level.[27] 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.

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

[27] 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.[28] 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[29] 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.[30] 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.[31]

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

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

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

[31] 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 presents the first principal component loadings from Principal Component Analysis (PCA) for the 23 monthly aggregated net sentiment variables from January 2012 to December 2024.[32] Panel A ranks the loadings in descending order of their magnitude. 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.[33]

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

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

[33] 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 3 Continued

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**

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.[34] The predictions are based on the model presented below.[35]

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

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

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

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).[36] The pillar exposures sentiment timing skills (Cao et al., 2013 [CCLL]) is estimated using the following equations:

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

f_t represents the nine hedge fund factors selected by Chen et al. (2025).[37] 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.

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[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.
[35] 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.
[36] 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/).
[37] I 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:

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

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

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.[38] $\Delta Sentiment_{it}^X$ 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).[39] 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.

[38] For $\gamma_{it}^{XST;\,HM}$, I 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).

[39] I 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[40]

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

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).[41] 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.

[40] $Flow_{it} = \frac{Assets_{i,t} - Assets_{i,t-1} * (1+Return_{i,t})}{Assets_{i,t-1}}$. *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.

[41] Specifically, the investor sentiment timing skill is captured by $\hat{\gamma}^{Investor}$, as defined in the equation below:

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

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/).

	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%		

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.[42]

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

$\hat{\gamma}_{it-1}^{XST}$ is the estimated pillar timing skills (CCLL) for fund i in month $t-1$. $\boldsymbol{X}_{\boldsymbol{AFI}}$ represents a set of 129 variables capturing funds' asset allocations, geographic focus, sector focus, investment focus, and investment approach indicators. 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). The variables in the results are ranked in descending order based on the magnitude of their absolute coefficient values.

[42] Since LASSO typically does not include fixed effects or clustered standard errors, I address this by calculating the average ESG timing skill for each fund, as well as the averages for each variable within the asset allocation, investment approach, investment focus, and geographic focus categories. I then regress the fund-level average ESG sentiment beta on these averaged asset and investment characteristics.

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

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).

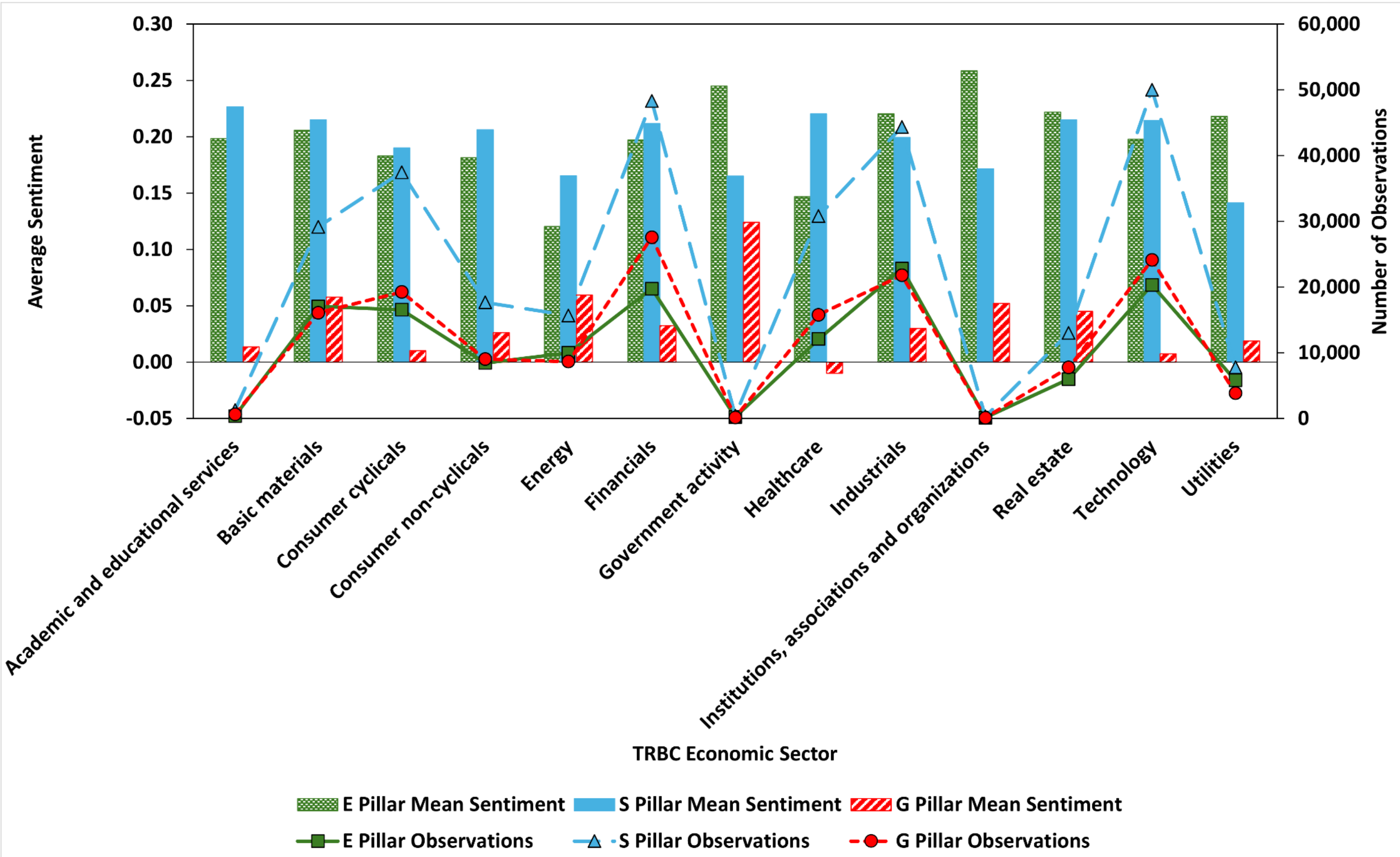
Table 2 Descriptive Statistics for Fund Assets Instruments and Focus Details

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.[43] 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).



[43] 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

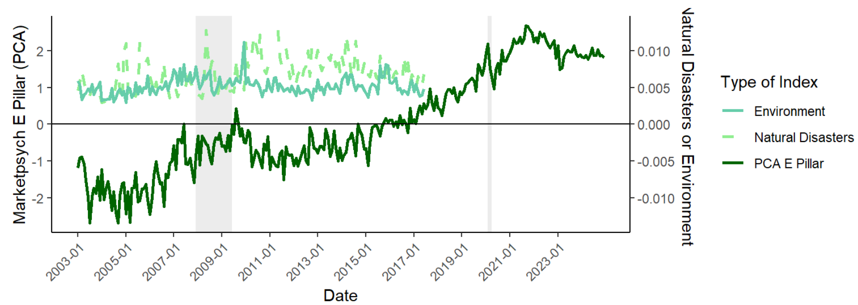


Figure 2B Social Pillar, Gender Issues, and Diseases Topic Indices

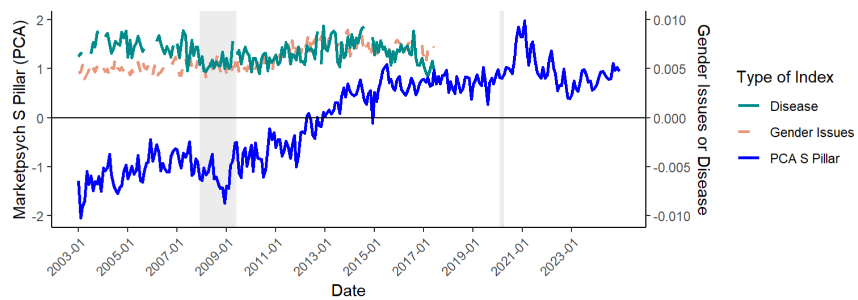


Figure 2C Governance Pillar, Bankruptcy, and Corrections/Amplifications Topic Indices

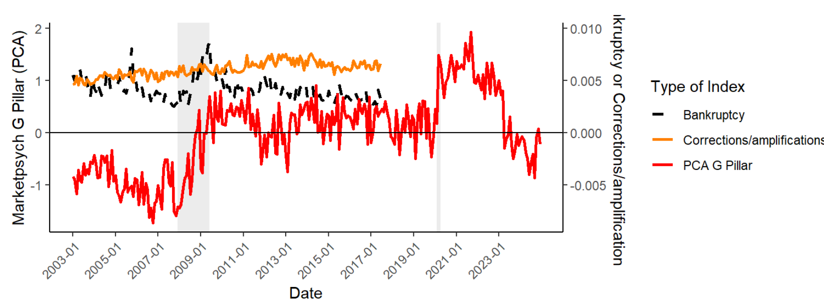


Table 3 Pillar Sentiment Betas and Topic Indices Predicting Performance and Risks

This table presents the prediction of funds' future performance and risks[44] 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.

[44] 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.
$Flow_{it} = \frac{Assets_{i,t} - Assets_{i,t-1} * (1 + Return_{i,t})}{Assets_{i,t-1}}$.

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	
$\hat{\gamma}^{EST} \times$												
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	
$\hat{\gamma}^{EST} \times$												
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	
$\hat{\gamma}^{SST}$ ×												
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	
$\hat{\gamma}^{SST}$ ×												
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	
$\hat{\gamma}^{GST} \times$												
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	
$\hat{\gamma}^{GST} \times$												
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%		