When Social Risks Matter: Retail Fund Flows and Social Concern[⋆]

David Ardia[a], Keven Bluteau[b], Céleste Hardy[c,*], Marie Lambert[c]

[a] *CIRANO & GERAD & Department of Decision Sciences, HEC Montréal, Montréal, Canada*
[b] *Department of Finance, Université de Sherbrooke, Sherbrooke, Canada*
[c] *HEC Liège, Management School of the University of Liège, Liège, Belgium.*

Abstract

Do retail investors care about the social value or social values of their investments? This paper builds a novel Human Capital Concern (HCC) index that captures public concern about financially material social risks and analyzes U.S. mutual fund flows of retail investors from 2015 to 2023. It shows that flow sensitivity to funds' social risk scores increases by 60% during periods of elevated human capital concern. Our research reveals non-linear effects in the intensity and duration of the HCC index, suggesting that investors mostly react to shock in the news regarding social risks. Funds with stronger social performance earn higher returns following high-HCC periods, with effects persisting for only two months. This pattern is consistent with a discount-rate news channel in which investors update their expectations about the future returns of high- versus low-social-risk assets.

Keywords: Human Capital, Social Risk, Investor Behavior, Mutual Fund Flows, Retail Investors, News-Based Measures

[⋆] We thank participants at the AFFI (2024) conference, the GRASFI PhD workshop (2024), FMA Europe (2025) conference, and CSBF (2025). We also thank FNRS, IVADO, MITACS, and the Natural Sciences and Engineering Research Council of Canada (grant RGPIN-2022-03767) for their financial support.

[*] Corresponding author. HEC Liège - Management School of the University of Liège, 14 Rue Louvrex, 4000 Liège, Belgium

Email addresses: david.ardia@hec.ca (David Ardia), keven.bluteau@usherbrooke.ca (Keven Bluteau), celeste.hardy@uliege.be (Céleste Hardy), marie.lambert@uliege.be (Marie Lambert)

1. Introduction

Despite widespread claims that investors increasingly seek exposure to the social dimension of ESG (Financial Times, 2022), little is known about whether social considerations meaningfully affect actual portfolio choices. Using data on U.S. mutual funds, we show that retail investor flows become more sensitive to funds' social risk when public concern about human capital issues is more salient. Assessing the relevance of social criteria in retail investment decision is particularly important given the fiduciary duty of the asset management industry, which may extend to ESG considerations when they are financially material.

Whether retail investors incorporate ESG criteria for financial or non-pecuniary reasons remains debated. Early studies interpret retail investors' attention to sustainability metrics as reflecting non-pecuniary preferences (Riedl and Smeets, 2017; Rossi et al., 2019; Bauer et al., 2021). In contrast, more recent evidence suggests that retail investors respond to ESG-related information primarily when it has financial implications (Li et al., 2024). This paper reconciles these views by examining whether retail investors perceive the social performance of their investments in mutual funds as financially material. Social dimensions have often been associated only with ethical motivations.

We examine retail and institutional flows into 5,014 U.S.-domiciled equity mutual funds over the period 2015–2023, with our primary focus on retail funds. Our analysis focuses on retail investors, as they account for approximately 88% of total assets invested in U.S. mutual funds. This makes mutual fund flows a natural setting for studying the sensitivity of retail investors to the social characteristics of their investments. Under the limited-attention framework (Kahneman and Tversky, 1979; Shefrin and Statman, 2000; Hirshleifer and Teoh, 2003), retail investors are subject to cognitive biases. Prior research shows that investor behavior is influenced by media coverage and short-term information signals (Da et al., 2011; Peress, 2014; Docherty and Hurst, 2018; Barber et al., 2022), and that investors disproportionately allocate capital to attention-grabbing stocks and "hot style" investment funds (Cooper et al., 2005; Barber and Odean, 2008). Exploiting this insight, we implement a quasi-natural experiment on investor attention by constructing a novel news-based index that tracks time variation in media attention to human capital risks using two major U.S. newspapers, The Wall Street Journal and The New York Times. In September 2023, The Wall Street Journal recorded the highest average weekday print circulation among U.S. newspapers (555.2 thousand), followed by The New York Times (267.6 thousand).[1]

Our Human Capital Concern (HCC) index tracks the time variation in concern about human capital issues by combining a sentiment lexicon, which captures negative tone, with a risk lexicon that identifies discussions of adverse events. We focus on human capital because it is among the most economically relevant components of the social pillar of ESG. A large body of financial literature documents the importance of human capital for firm performance and risk (Edmans, 2011; Shan and Tang, 2023; Edmans et al., 2024), and this dimension is explicitly identified as a financially material by the Sustainability Accounting Standards Board (SASB).[2] To our knowledge, this index is the first to specifically capture concern related to the social dimension of ESG.[3]

Our empirical setup is closely related to Li et al. (2024), but with two key distinctions. First, we explicitly focus on the social dimension of ESG. To measure social performance, we rely on Morningstar's social risk scores, which are readily accessible to investors through ESG rating agencies. Second, we study retail investors' allocation decisions using mutual fund flows rather than individual trading orders. In light of Sloan (2024), this setting is particularly well-suited to assess whether retail investors treat social performance as financially material.

Estimating a panel regression of mutual fund flows, we find that investors' sensitivity to social performance varies systematically with the level, intensity, and duration of shocks in media attention to human capital issues. Allowing for nonlinear effects using a Generalized Additive Model, we show that flow sensitivity to social performance becomes economically and statistically significant only at elevated levels of concern. Quantitatively, a one-standard-deviation increase in HCC raises the sensitivity of flows to social scores by more than 60%. We interpret this increased sensitivity to social risk as an evidence that retail investors care

[1]See `https://www.statista.com/statistics/272790/circulation-of-the-biggest-daily-newspapers-in-the-us/`.

[2]The SASB identifies five sustainable dimensions, namely Environment, Social Capital, Human Capital, Business Model and Innovation, Leadership and Governance; see `https://www.sasb.org/standards/materiality-finder/find/?lang=en-us`.

[3]Textual analysis has been widely used to construct environmental and ESG-related indices (Engle et al., 2020; Ardia et al., 2023; De Nard et al., 2024; Sautner et al., 2023; Faccini et al., 2023), but no comparable index exists for the social pillar.

about the social value of their investments.

An alternative interpretation of our results could be that investors incorporate social considerations into their investment decisions for moral reasons. According to the moral development theory (Kohlberg, 1981), individuals form ethical values in different stages of their development. that might influence capital allocation. Moral motivations are generally stable, linked to identity and self-image (Brekke et al., 2003; Akerlof and Kranton, 2000; Mayr and Freund, 2020). These theoretical frameworks suggest that values-driven investors should maintain their capital allocation despite fluctuations in media attention. Consistent with this view, previous evidence shows that investors increasingly align portfolios with social values and that social identification influences risk perceptions (Bauer and Smeets, 2015; Bonnefon et al., 2025). The conditional sensitivity of fund flows to social criteria seems difficult to reconcile with this channel, implying only values-driven motivations. Finally, it could also be that the Morningstar measure does not assess the social risk of investment funds, but rather captures a general assessment of the sustainable performance of the fund. However, we show that in periods of elevated social concern, fund flow sensitivity to ESG labeling in fund names decreases, whereas the fund flow sensitivity to the social risk measure increases.

We rather propose the existence of a risk channel through which media coverage draws retail investor attention to the financial materiality of macro-level social concern risks. We further show that after periods of elevated human capital concern, funds with higher social scores earn higher returns for about two months. We rule out the possibility that these additional returns are driven by additional fund inflows or superior manager skills. Our findings suggest a revision of risk premiums associated with the social performance of financial assets during periods of increasing human capital concern. In addition, our analysis indicates that investors are, on average, averse to social risk, as reflected in the increased return sensitivity to our social risk measure during periods of concern.

To consolidate the financial channel, we construct an alternative news-based index capturing media attention to ethical issues such as human rights and individual freedoms. These issues, grouped under the Social Capital dimension, are also recognized as financially material in the SASB Materiality Map, but for a smaller set of industries than Human Capital. We find that the sensitivity of flows to social scores does not vary significantly with Human

Rights Concern (HRC) levels. This further supports our interpretation that retail investors' increased sensitivity towards the social risk performance of investment funds is primarily driven by perceived financial materiality rather than ethical considerations.

This paper contributes to the debate highlighted in Starks' (2023) AFA presidential address on value versus values when considering sustainability criteria. This debate resonates with a growing body of literature seeking to disentangle financial and non-financial motivations behind sustainable investing. Our findings show that retail investors' attention to social factors is state-dependent, increasing when social risks become financially salient and fading when ethical concern lacks clear financial materiality. These results do not imply that investors disregard ethical values, but rather that the observed capital reallocation pattern is consistent with responses to perceived financial materiality in social risks.

More broadly, this paper relates to the literature on investor interest in sustainability and the role of non-financial criteria in investment decisions (Hartzmark and Sussman, 2019; Ammann et al., 2019; Ceccarelli et al., 2024). Recent work suggests that investor attention to ESG scores may fade over time (Gantchev et al., 2024), but this literature does not account for the time-varying relevance of sustainability considerations. Other studies document greater investor loyalty to ESG performers than to non-ESG funds (Bollen, 2007; Benson and Humphrey, 2008). We contribute to this strand by investigating whether investor sensitivity to social performance is conditional on the emergence of financially material social risks.

The remainder of the paper is organized as follows. Section 2 describes the construction of the news-based index capturing human capital concern. Section 3 presents the data. Section 4 reports the empirical results on the time-varying sensitivity of mutual fund flows to social performance. Section 5 investigates the information content of social risk scores and evaluates alternative economic channels. Section 6 provides additional robustness tests. Section 7 concludes.

2. Measuring media concern about social issues

We develop a novel index of social concern following Ardia et al. (2023). To our knowledge, this is the first index to specifically capture concern related to the social dimension of ESG. We rely on the framework from the SASB to define the social dimensions that are considered as financially material for investors and focus on human capital issues (i.e., Labor Practices, Employees Health and Safety and Employee Engagement, Diversity & Inclusion). Using the subject classification of Factiva to create our corpus of news, we focus on media articles belonging to the "work and staff" category. This category includes news discussing topics related to employee retention, health and safety at work, social conflicts, discrimination and professional abuses, layoffs, remuneration, recruitment, training and employee development, business-to-employee relations, professional diversity as well as professional misconduct. Our sample of news includes 16,147 articles from two of the most influential newspapers in the United States: The New York Times (NYT) and the Wall Street Journal (WSJ). These newspapers differ significantly in their focus, audience, and editorial approach. The NYT is a general-interest newspaper with a liberal (center-left) editorial line, exploring the human and cultural impact of events and policies. In contrast, the WSJ is traditionally considered a right-leaning newspaper covering economic and financial topics. Our sample includes English-language articles and covers the period between January 1st, 2010, and June 30th, 2024. Similar to Ardia et al. (2023), we measure the perception of risk and the negative sentiment to extract the concern around the social dimension.[4]

Relying on a lexicon-based approach for extracting social concern in news articles offers several advantages over large language models (LLMs) like BERT or ChatGPT, particularly in terms of transparency, efficiency/cost, and reliability (Ardia et al., 2023). Unlike LLMs, which function as black boxes, lexicon-based methods provide interpretable and consistent results by relying on predefined word lists, making them easier to explain. They require minimal computational resources, making them more efficient for large-scale analysis without expensive GPUs or extensive training data. Additionally, lexicon-based approaches ensure reproducibility and eliminate the risk of hallucinations often seen in LLMs.

We assume a media universe of two news sources $s = 1, 2$, namely the WSJ and the NYT. On each day $t = 1, \ldots, T$, source s publishes $n = 1, \ldots, N_{t,s}$ articles discussing human capital issues. To assess the level of concern, we consider both the risk lexicon (i.e., to assess the level of discussion about risk events) and the sentiment lexicon (i.e., to evaluate the increase

[4] As Ardia et al. (2023), we use LIWC-22 lexicons (Pennebaker et al., 2015) to quantify affective tone and risk-related language; see `https://www.liwc.app`.

in risk perception). Consistent with Ardia et al. (2023), the concern is thus computed as follows:

$$\text{Concerns}_{n,t,s} = 100 \times \left(\frac{\text{Risk Words}_{n,t,s}}{\text{Total Words}_{n,t,s}}\right) \times \left(\frac{\text{Neg. Words}_{n,t,s} - \text{Pos. Words}_{n,t,s}}{\text{Neg. Words}_{n,t,s} + \text{Pos. Words}_{n,t,s}} + 1\right)/2. \quad (1)$$

The daily concern score for a given source s is then computed as the sum of article-level concern scores for each day t. This aggregation captures both the level of media attention to human capital through the number of news articles published about human capital issues on day t by source s ($N_{t,s}$) and the average level of concern expressed in news articles on a given day t for a given source s ($\overline{\text{Concerns}}_{t,s}$).

$$\text{Concerns}_{t,s} = \sum_{n=1}^{N_{t,s}} \text{Concerns}_{n,t,s} = N_{t,s} \times \overline{\text{Concerns}}_{t,s}\,. \quad (2)$$

The final step involves aggregating the source-specific indices to compute the Human Capital Concern (HCC) index for each day t. To address source heterogeneity in baseline reporting patterns, we apply the source-aggregation methodology of Baker et al. (2016). First, we compute the standard deviation of each source-specific index over 2010–2015. Second, we use these source-specific standard deviations to standardize each index over the full sample period. This source-specific normalization captures relative changes in the coverage intensity of human capital news and is therefore a crucial step for the subsequent aggregation of individual source indices. This approach prioritizes the temporal variations within each source rather than absolute differences between sources, thereby enhancing our ability to detect meaningful shifts in human capital coverage. We refer to Ardia et al. (2023), Section 2.3., for more details.

Finally, we compute the HCC index on day t by taking the square root of the average of the normalized source-specific concern for that day to account for the fact that increased media attention always strengthens concern, but at a decreasing rate. This gives us a daily index that we aggregate at the monthly level to perform our analysis of fund flows. Figure 1 plots the resulting monthly HCC index. The index shows significant spikes in response to events related to human capital, such as the 2016 Verizon workers' strike, Starbucks' store closures for racial bias training in May 2018, the Brumadinho disaster (one of the deadliest mining accidents in history), or the concern around workforce management during the COVID-19 outbreak.

[Insert Figure 1 about here.]

Table 1 reports statistics about the number of "work and staff" articles published by the two sources in our sample. The WSJ publishes more articles about work and staff than the NYT, with 10,165 articles. This represents 2.17% of its total number of articles compared to only 0.70% for the NYT. Table 1 also reports information on the concern, sentiment, and risk scores extracted from the articles published by both sources. In particular, we see that the average concern (sentiment) score is 0.31 (0.40) for the WSJ and 0.35 (0.45) for the NYT. The percentage of articles with a zero concern score is much larger for the WSJ than for the other outlet. This suggests that the WSJ employs a less opinionated tone and utilizes less fatalistic language compared to the NYT. These discrepancies in news reporting, both in terms of coverage and information treatment, justify the need for standardization by source before aggregation.

[Insert Table 1 about here.]

For robustness, we verify that HCC is largely orthogonal to broad macroeconomic conditions by regressing monthly changes in HCC on contemporaneous changes in unemployment, market volatility (VIX), consumer price inflation (CPI), and the Economic Policy Uncertainty (EPU) index. The results, reported in Appendix B, show economically small coefficients and a low R^2, confirming that HCC captures idiosyncratic social attention rather than general economic stress.

3. Mutual fund data

Our study relies on mutual funds' characteristics and sustainability scores from the Morningstar Direct database.

3.1. Morningstar Direct

Sourcing from Morningstar Direct, we collect data for all open-end equity mutual funds domiciled in the U.S. over the period from January 2015 to May 2023. For each fund, we retrieve information on its monthly return and monthly total net assets (TNA) to compute investment flows. We additionally collect information such as inception date, fund domicile, star rating, investment style, sustainability information and the share class type. Following Hartzmark and Sussman (2019), we aggregate the data of funds offering multiple share classes to perform the analysis at the fund level. The *FundID* provided by Morningstar has been used as the main basis to perform this aggregation. Fund total net assets are calculated as the sum of the TNA across the fund's share classes, while other characteristics are computed as the mean value of the various share classes. The fund age is calculated from the inception date of the oldest share class. If the fund offers both institutional and non-institutional share classes, we separately aggregate share-level information as one institutional fund and one retail fund.[5] Our sample period is limited by the availability of ESG data, which started being available in January 2015. Besides, our sample is restricted to funds having at least one environmental and a social score over the sample period. After retaining funds with valid Morningstar sustainability information, we end up with a sample of 3,915 retail and 3,288 institutional funds over the period from January 2015 to May 2023. The main focus of our paper is on the sample of retail mutual funds.

Following prior literature, we calculate the net investment flows of fund i in month t as the percentage growth of new assets beyond reinvested returns, assuming that all flows take place at the end of the month. Formally, it is calculated as:

$$\text{Flow } (\%)_{i,t} = \frac{\text{TNA}_{i,t}}{\text{TNA}_{i,t-1}} - (1 + R_{i,t}) \,, \tag{3}$$

where $\text{TNA}_{i,t}$ is the total net assets under management of fund i at the end of month t, and $R_{i,t}$ is the total return of fund i in month t. To mitigate the influence of outliers, flows and returns are winsorized at the 1% and 99% levels.

[5] A fund share class is considered as institutional if the Share Class Type variable is "Instit". Other types of share class are considered as retail shares.

3.2. Morningstar sustainability scores

To assess the non-financial performance of mutual funds, we retrieve the ESG, environmental, and social risk scores provided by Morningstar. These scores are computed as the asset-weighted average of Sustainalytics' Company Environmental / Social scores for the corporate holdings in the portfolio.[6] We use Morningstar sustainability metrics exclusively, as merging with alternative datasets such as Refinitiv or MSCI would substantially reduce our sample. Furthermore, Morningstar is widely regarded as a leading source for investment fund analysis. The platform is extensively used by institutional investors, fund managers, and academics, making it a standard reference in the field. The direct integration of sustainability information with financial data further enhances its utility for analyses combining financial and non-financial criteria.

An important consideration regarding the ESG risk scores used in this analysis is the methodological shift implemented by Sustainalytics and its subsequent adoption by Morningstar in September 2019. Under the old methodology, companies were assessed based on their ability to manage ESG risks and opportunities within their respective industries. Under this approach, scores ranged from 0 to 100, where a higher score indicated stronger sustainability practices and lower risk exposure.

The revised methodology introduced a fundamental change in how ESG risks are measured. Instead of focusing on management effectiveness, the new Environmental and Social Risk Scores quantify the degree to which a company's economic value is at risk due to environmental or social factors. These scores intend to reflect the portion of environmental and social risks that remain unmanaged after accounting for a company's mitigation efforts. While the numerical scale still ranges from 0 to 100, it has been inverted since September 2019, with most values falling between 0 and 25. Under this framework, lower scores indicate lower exposure to ESG-related financial risks, while higher scores signify greater vulnerability.

Given this change in methodology, the scores before and after September 2019 are not directly comparable. To ensure consistency across our dataset, we compute the percentile

[6] See `https://www.morningstar.com/investing-definitions/portfolio-social-risk-score` and `https://www.morningstar.com/investing-definitions/portfolio-environmental-risk-score`.

rank of the scores on a monthly basis. Then, to align post-2019 scores with earlier values, we reverse the scale by inverting the percentiles. As a result, the interpretation of scores remains consistent throughout the entire sample period: a higher score corresponds to better ESG practices, reflecting a lower level of unmanaged ESG risk.

Panel A of Table 2 provides the summary statistics of funds characteristics for the full sample. The average fund in our sample has a net return of 0.58% per month and registers, on average, a monthly net investment outflow of 0.21%.[7] The average fund is more than 16 years old and has assets under management amounting to nearly $2 billion. Panels B and C of Table 2 describe retail and institutional funds characteristics, respectively. On average, retail funds experience more outflows, have a lower Star rating, are 5 years older, and are slightly larger than institutional funds. On average, both types of funds have similar monthly returns.

[Insert Table 2 about here.]

Table 3 describes how the sustainability metrics are distributed across the sample. Panel A provides summary statistics for these characteristics for all funds in our sample from January 2015 to September 2019, that is, before the methodological change. Panel B provides the distribution for all funds in our sample after September 2019. The average fund has a social (environmental and ESG) score of 50.90 (52.00 and 46.20) before September 2019 and a score of 8.49 (4.18 and 23.20) after this date. Panel C describes the transformation into percentile ranks that mitigates scale differences and temporal variations by providing a standardized distribution, with the average fund having a score of 0.50.

[Insert Table 3 about here.]

4. Fund flows, social risk and human capital concern

We estimate the cross-sectional sensitivity of mutual fund flows to sustainability performance (social and ESG scores) at each time t. Specifically, we relate contemporaneous net

[7] We validate our sample by reconciling the sample used in Hartzmark and Sussman (2019) from March 2016 to January 2017 with a subset of our sample.

flows to lagged measures of social performance while conditioning on standard fund characteristics. This approach exploits the cross-sectional variation between funds within a given month. The model stands as follows:

$$\mathrm{Flow}_{i,t} = \alpha_i + \beta_1 \mathrm{Soc}_{i,t-1} + \beta_2 \mathrm{CTRL}_{i,t-1} + \varepsilon_{i,t}\,, \tag{4}$$

where, $\mathrm{Flow}_{i,t}$ denotes the percentage net flow of fund i in month t. The key independent variable, $\mathrm{Soc}_{i,t-1}$, is the percentile of the social (risk) score of fund i in month $t-1$. Using lagged sustainability measures, we mitigate concerns about the simultaneity between flows and sustainability scores. $\mathrm{CTRL}_{i,t-1}$ accounts for the usual flow drivers at time $t-1$: the logarithm of the total net assets (TNA) in the fund i, the logarithm of fund's age (in months since inception date), and the past performance of the fund i measured as the one-month lagged raw return and Morningstar Stars rating.[8] The lagged return accounts for short-term performance, whereas the Morningstar star rating accounts for the performance over a longer period of time. We include the environmental score as a control variable to isolate the specific effect of the social factor. To control for the fact that fund flows within a style category are correlated with the past returns of that style category (Teo and Woo, 2004), we introduce investment style fixed effects corresponding to the nine Morningstar-style boxes.

We group the monthly estimates of flow sensitivity β_1 into three buckets, based on the terciles of the level of HCC to which the month belongs, and average the monthly estimates in each bucket. Figure 2 reports the average values of the sensitivity to flow-sustainability, along with their 95% confidence intervals, by terciles of social concern. Panel A reveals a nonlinear upward-sloping relationship between flow sensitivity and social performance across HCC terciles. During periods of low social concern (first tercile), flow sensitivity to social scores is slightly negative at -0.05 and statistically indistinguishable from zero, indicating that investors neither reward nor penalize funds based on social performance when workforce-related risks are not salient. As concern rises to a moderate level (second tercile), the sensitivity be-

[8]We follow previous research and include the Morningstar rating as a continuous variable (Del Guercio and Tkac, 2008; Pastor and Vorsatz, 2020; Döttling and Kim, 2024). However, as the relationship is convex, we repeated the analyses by including binary variables for each star level (from 1 to 5) or by including a squared term as an additional control variable. The results are non-tabulated but remain similar across all specifications.

comes weakly positive (0.10), though confidence intervals remain wide. However, when HCC reaches its highest tercile, the sensitivity surges to 0.46. This convex shape suggests that the impact of social performance on fund flows is minimal for low levels of HCC, but becomes increasingly important when public concern about macro-level social issues rises. Using the overall ESG score as an additional test, Panel B corroborates this pattern. Although flow-sensitivity remains negative across the bottom three HCC terciles, it becomes positive in the top terciles, supporting the conclusion that the ESG performance-flow relationship strengthens in times of high levels of HCC. Collectively, both panels suggest that investor sensitivity to non-financial performance metrics is contingent upon the level of human capital concern conveyed by the media.

[Insert Figure 2 about here.]

4.1. Panel analysis

Given these preliminary results, we formally test whether the flow sensitivity to social performance is conditional on the level of HCC using the following panel regression. The regression model is written as follows:

$$\text{Flow}_{i,t} = \alpha_i + \beta_1 \text{Soc}_{i,t-1} + \beta_2 \text{HCC}_{t-1} + \beta_3 (\text{Soc}_{i,t-1} \times \text{HCC}_{t-1}) + \beta_4 \text{CTRL}_{i,t-1} + \varepsilon_{i,t}\,, \quad (5)$$

where, $\text{Soc}_{i,t-1}$ is our social performance metric at time $t-1$. HCC_{t-1} corresponds to our HCC index in month $t-1$. In addition, we include time-fixed effects to capture the potential time trends in mutual fund flows. By including style-by-time fixed effects, we account for time-varying aggregate flows in and out of the mutual fund industry, as well as shifts in allocations across different investment styles.

Table 4 presents the results of Equation (5). The coefficient β_1 corresponds to the sensitivity of the fund flow to the social score in times of average social concern level. The interaction term $\text{Soc}_{i,t-1} \times \text{HCC}_{t-1}$ captures how the flow-sustainability sensitivity depends on the level of global concern about social issues.

[Insert Table 4 about here.]

In general, we observe that mutual funds with higher social (risk) performance receive larger flows than funds with lower social performance. In addition, the interaction term $\text{Soc}_{i,t-1} \times \text{HCC}_{t-1}$ is positive in all specifications. This indicates that mutual fund flows become more sensitive to social scores in times of rising public concern about macro-level social issues (proxied by the *HCC* variable).

We show that the results are robust to the inclusion of either style fixed effects or time fixed effects (see Columns 1 and 2). In Column 3, we introduce style-by-time fixed effects, which compare funds within the same investment style in a given month. This specification absorbs common shocks at the style-month level and therefore isolates within-style cross-sectional variation. Although the interaction term becomes statistically weaker in this specification, its magnitude remains economically similar.[9]

In Columns 4 and 5, we control for the COVID-19 crisis as the HCC index peaks at this time period (from January 2020 to July 2020). This suggests a significant shift in public concern towards social issues such as health, inequality, and working conditions. We isolate this period to ensure that our overall results are not driven by this exceptional period.[10] We add a COVID dummy and its interaction with Soc_{t-1} to capture the effect.[11] Controlling for the specific impact of the COVID-19 crisis, fund flows become even more sensitive to social scores in times of elevated concern. An increase of one standard deviation in *Soc* is associated with a 7.3 basis points increase in net flows (Column 4). Besides, the coefficient of the interaction term indicates that for each additional one-standard-deviation increase in *HCC*, the sensitivity of fund flow to social performance rises by 4.2 basis points. In other words, the consideration of social performance in investment decisions is strengthened by about 60% (0.042/0.073) following a one-standard-deviation increase in HCC level.

In Column 5, we further interact HCC with other performance metrics (*Return*, *Star*, *Env*) as they can be correlated with the fund's social performance.[12] The cross-effects

[9] The interaction remains statistically significant when clustering is relaxed, indicating that the reduction in significance is attributable to the higher variance induced by fund-level clustering rather than to the absorption of style-time variation.

[10] We get similar results when following Pastor and Vorsatz (2020) COVID-19 time window going from February 2020 to May 2020.

[11] For ease of readability, we report the coefficients of the interaction with the COVID-19 dummy Appendix D.

[12] The correlation matrix is available in Appendix Appendix E.

of *HCC* and financial performance are significantly positive, whereas the interaction with environmental score is not. When the social concern is at its average value (HCC = 0), the sensitivity of fund flows to return is positive. Specifically, a one-standard-deviation increase in lagged monthly returns is associated with an increase in net flows by 36.1 basis points. In addition, a one-standard-deviation increase in star rating boosts flows by 70.9 basis points. This means that when *HCC* is average, funds with better financial performance attract significantly higher flows. The interaction effect of the lagged star rating with our HCC index is positive and significant. This suggests that greater public concern for human capital issues (such as labor practices, employee well-being, and diversity) is associated with a greater focus on financial performance.

Our empirical setup is specifically intended to test whether investors attach financial materiality to social risks. By examining monthly fund flows, our approach addresses Sloan (2024) point that nonpecuniary preferences are rarely expressed through day trading and are more likely implemented via investment funds. We therefore interpret our findings as evidence that investors do treat social risk as financially material during periods of public concern about macro-level social issues.

In addition, we address identification concerns with two complementary tests. The results are available in the Appendices. First, we residualize the HCC index with respect to standard macroeconomic and policy controls and re-estimate our baseline models. The coefficients remain economically and statistically unchanged, indicating that our results are not driven by aggregate conditions or correlated macroeconomic shocks (See Appendix F. Second, we conduct permutation-based placebo tests by randomly reshuffling HCC across time (globally and within funds). In 1,000 iterations, the distribution of placebo interaction coefficients is tightly centered around zero and never approaches the magnitude of the true estimate, yielding an empirical p-value of zero (See Appendix G. Together, these tests confirm that our findings are robust and unlikely to reflect spurious time variation or random alignment.

4.2. Intensity and duration of the HCC index

The previous subsection shows that sensitivity to social performance score increases in times of social concern. We define shocks in the public concern about social issues based on the intensity of the HCC. We define four thresholds to characterize these shocks: *Very low*,

Low, *Moderate*, and *Severe*. A shock is defined as *Very low* when the HCC value is lower than one standard deviation away from the average, *Low* when the HCC value is between one standard deviation below the average and the average, *Moderate* when the HCC value is between the average and one standard deviation above the average, and *Severe* when the HCC value is higher than one standard deviation above the average. We replicate the analysis considering these shock intensities in Table 5.

[Insert Table 5 about here.]

The regression results reveal that the sensitivity of fund flows to social performance triples after severe human capital shocks compared to periods of below-average HCC. By comparison, the effect during Moderate HCC periods is small and not statistically significant, indicating that only extreme social concern shocks meaningfully amplify investors' responsiveness to social factors. Moving from Columns 1 to 3, we show that the results are robust to style-, time-, and style by time-fixed effects.

To explicitly capture this nonlinearity, we complement our linear fixed-effects models with a Generalized Additive Model (GAM) regression, allowing for flexible functional forms in the interaction between human capital concern and social scores. The GAM results are presented in Figure 3.

Figure 3 illustrates the estimated nonlinear effects of the social score on fund flows, conditional on the intensity level of the HCC. The curves indicate how deviations in the social score are associated with changes in fund flows. We observe that all groups display a positive association between higher social scores and fund flows, but the magnitude of the effect differs substantially with the intensity of the HCC. When the HCC is very low to low, the slope is relatively flat, suggesting limited investor response to social performance. The effect becomes slightly more pronounced under moderate shocks and increases sharply during severe HCC shocks. In these periods, funds with low social scores experience weak or even negative predicted flows, whereas high-scoring funds attract larger inflows. Economically, moving from the 25th to the 75th percentile of the social score generates only modest changes in predicted flows during low-HCC periods, but produces larger net flows during severe-HCC shocks. These patterns reinforce the interaction results reported in Table 5 and indicate that increasing attention to human capital (risk) issues amplifies investor sensitivity to social performance.

[Insert Figure 3 about here.]

In addition, we can qualify HCC shocks based on their duration. We consider two duration levels for the shock: a short shock is when the HCC index level goes within the defined intensity range for one month and returns out of this range in the following month. A shock is considered long when the HCC index spikes within the range and remains within this range for more than one period. We interact the duration of the HCC shocks with Soc_{t-1} for different intensity ranges. The results are available in H.17. We find that the flow sensitivity only increases in times of severe and long-lasting shocks. The insignificance of short-lived shocks suggests that transitory spikes in public concern about social issues do not trigger a reallocation of capital toward high-sustainability funds. These findings indicate that investors respond not merely to the level of social concern but to its persistence. It suggests that short-lived spikes are insufficient to alter portfolio allocations at a monthly frequency, whereas severe and sustained HCC shocks likely signal structural shifts in the relevance of social risks.

5. The information content of social risk score in times of social concern

We evaluate whether investors benefit from reallocating capital in response to increased social concern. We hypothesize that if funds with stronger social performance consistently exhibit positive returns following periods of elevated HCC, it would indicate that a higher social score in times of HCC conveys information about future fund return.

We regress future fund returns on fund social score and its interaction with HCC. The regression stands as follows:

$$\text{Return}_{i,t+h} = \alpha_i + \beta_1 \text{Soc}_{i,t-1} + \beta_2 \text{HCC}_{t-1} + \beta_3 (\text{Soc}_{i,t-1} \times \text{HCC}_{t-1}) + \beta_4 \text{CTRL}_{i,t-1} + \varepsilon_{i,t} \,, \quad (6)$$

where, $\text{Return}_{i,t+h}$ is the dependent variable and represents the return of fund i in month $t+h$, with $h \in \{0, 1, 2, 3, 4\}$. Other variables are defined as in previous regression models.

Table 7 presents the results from period t to $t+4$. The interaction term between HCC and the social score is positive and statistically significant from t to $t+2$. By $t+3$, the estimate becomes small and statistically insignificant, indicating that the effect vanishes beyond a two-month horizon. A high social score acts as a short-term positive signal for subsequent returns when human capital issues are salient.

[Insert Table 7 about here.]

Three interrelated economic mechanisms could explain the increase in returns associated with high social scores during periods of elevated social concern.

A first mechanism could be a fund-level demand channel. When attention to social issues intensifies, investors may perceive the social performance of their investment as a financially relevant attribute and reallocate capital to funds with strong social profiles. Such demand shocks can increase the valuations of the holdings of funds with high social scores, which are themselves likely to exhibit strong social performance. The resulting capital inflows may, in turn, generate temporary return effects at the fund level (Baker and Wurgler, 2006; Pedersen et al., 2021).

To assess this mechanism, we perform a causal mediation analysis in which fund flows act as the mediator between the interaction term $HCC \times Soc$ and future fund returns. The results are reported in Table 8. The Average Causal Mediation Effect (ACME) is positive and statistically significant, indicating that part of the return effect operates through fund flows. However, its magnitude is economically small relative to the total effect. The mediated component only represents about 3% of the overall impact of $HCC \times Soc$ on future returns.

[Insert Table 8 about here.]

A second economic mechanism could be that the post-return drift of funds with high social scores is driven by managerial skill. Under this mechanism, fund managers exploit opportunities within the ESG universe that become valuable during periods of heightened social concern. If this channel was driving our results, the return effect should be concentrated among actively managed funds (Berk and Green, 2004). To investigate this channel, we replicate the analysis of Table 7 on passive index funds and ETFs. Because these types of funds do not rely on discretionary stock selection, their performance should not reflect managerial skill. Panel A and Panel B of Table 9 provide the results for index funds and ETFs, respectively. Although none of these funds exhibit increased flow sensitivity to social performance in times of social concern, they display similar return dynamics as retail funds.[13] The presence of the same temporary positive returns among passive vehicles, which do not engage in discretionary stock selection and receive minimal flows, is inconsistent with both the managerial skill channel and the fund-level demand channel.

Finally, a third mechanism could operate at the firm level. Increased attention to social issues increases the salience and perceived financial materiality of firms' social practices. In a rational asset-pricing framework, stock returns reflect revisions in expected cash flows and expected discount rates (Campbell and Shiller, 1988; Campbell, 1991). If heightened social concern increases the perceived relevance of social risk, the required return on firms with strong social characteristics may temporarily decline. Such a decrease in discount rates would generate contemporaneous valuation gains and subsequent return dynamics, even in the absence of fund-level flows. This interpretation is consistent with the equilibrium framework of Pastor et al. (2022), who show that shifts in investor preferences toward sustainable assets can alter equilibrium discount rates and generate temporary valuation gains for green firms when climate concern intensifies. Empirically, they document that green stocks tend to outperform brown ones following bad news about climate change, consistent with their role as partial hedges against climate shocks. Ardia et al. (2023) and Engle et al. (2020) provide supportive empirical evidence for this interpretation. Transposed to the social pillar, the return premium observed in our analysis could be interpreted as a temporary repricing of social risk when attention to social issues increases, followed by normalization as concern recedes. We further investigate this economic channel in the next section.

[Insert Table 9 about here.]

[13] Results on the flow sensitivity to social performance of index funds and ETFs are available in Appendix I.

6. Discussion of our results and alternative economic channels

We provide evidence that retail investors' sensitivity to the social (risk) performance of their fund allocations increases when public concern about social issues rises. Using fund-level returns, we show that funds with lower social risk (i.e., higher social scores) earn positive abnormal returns in times of rising concern. We rule out the possibility that these effects are driven by additional fund inflows or superior managerial skills. The return effect is short-lived and vanishes after two months.

Taken together, our findings suggest that shifts in public concern about social risks operate as discount rate news for individual securities under the present-value framework of Campbell and Shiller (1988).[14] The superior return of investment funds with high social performance following periods of social concern is consistent with a reassessment by investors of the relative riskiness of low-versus high-social-performance stocks, inducing a short-term price appreciation of stocks with high social performance, and, in turn, higher returns for investment funds holding these stocks.

Our interpretation relies on two key elements: (i) high levels of HCC provide discount rate news and draw retail investor attention to the financial relevance of macro-level social risks; and (ii) investors respond specifically to risk-related information and to changes in the perceived risk profile of their investments. We examine the robustness of these elements in the following sub-sections.

6.1. Alternative concern index

The discount rate news channel implies that the HCC is conveying information that is material for assessing the risk of financial assets. This means that if the index were not conveying such type of information, we would not observe any change in the sensitivity of flows to the social risks of the fund. We examine this situation by constructing an alternative index capturing media coverage of ethical issues.

We follow the same methodology used for the HCC index and replace the corpus of human capital-related news articles with articles from the "human rights and individual

[14] Campbell and Shiller (1988) derive a log-linear decomposition of the dividend–price ratio into expectations of future dividend growth and future returns.

freedoms" category. Although these issues are also classified under Social Capital in the SASB Materiality Map, the SASB framework suggests that they are less directly linked to firms' financial fundamentals than human capital–related issues in many industries.[15]

We re-estimate our baseline regression, replacing our HCC index with this novel values-oriented HRC index. Table 11 shows the results. Contrary to our previous results with the HCC, the fund flow sensitivity to social risk scores does not change with ethical concern. This suggests that retail investors primarily value the social performance of their investments for financial risk management purposes rather than for ethical considerations.

[Insert Table 11 about here.]

6.2. Investigating the risk channel

We further examine whether discount rate news prompts investors to reassess the underlying risk of the affected assets, and whether their response reflects risk-based considerations rather than purely social preferences. To do so, we replace the continuous social risk score in Equation 5 with a binary indicator, *ESG_Name*, capturing whether a fund adopts a sustainability-related term in its name.

Prior research shows that fund names can significantly influence investor capital allocation and serve as signals of investment strategy (Cooper et al., 2005). A positive reaction to the ESG labeling would suggest a preference-driven channel, contrary to the advocated risk channel. Table 12 presents the results.

[Insert Table 12 about here.]

The coefficients on $HCC_{t-1} \times ESG\_Name$ is significatly negative. This suggests that in periods of high financially material social risks, investors get more sensitive to the social risk assessment of their investments than their ESG labeling.

This analysis reveals a clear distinction in the investor consideration of social risk measures and sustainability labels. Fund flows respond positively to both metrics in general, but the interaction of each variable with HCC presents opposite signs. In contrast to social risk

[15]See Appendix III in Khan et al. (2016), which reports the sector-level SASB Materiality Map, where human rights issues are classified as financially material in 2 sectors out of 6 and for less than 50% of the industries within these sectors.

scores, the ESG label exhibits a negative interaction with HCC, indicating that funds with ESG-related terms in their names become less attractive as social risk exposure increases. Specifically, a one standard deviation increase in HCC completely reverses the consideration of the ESG label. In comparison, the sensitivity to the social risk score increases by 50-60%. This contrast in reaction reinforces the financially motivated, risk-hedging interpretation of our results.

6.3. Retail versus institutional investors

Finally, we examine whether the documented time variation in flow sensitivity to social performance is specific to retail investors. We therefore analyze institutional investors' response to social performance using our *HCC* index. Institutional investors face fiduciary duties and investment mandates that may constrain the integration of ESG considerations. Consistent with these constraints, prior evidence suggests that institutional investors adjust their portfolios to ESG information slowly over long horizons (Berg et al., 2024). By contrast, a large literature shows that retail investors trade more actively and respond strongly to attention-grabbing signals such as news or public information (Barber and Odean, 2008; Barber et al., 2022). Accordingly, we expect retail fund flows to be more sensitive to the level of social concern in the economy than institutional fund flows.

Table 10 reports the estimates of Equation (5) for institutional funds. In contrast to the retail sample, the interaction $Soc \times HCC$ is not statistically significant, indicating that institutional investors' consideration of social performance is not influenced by the level of social concern expressed in the media. Column 2 allows for nonlinear responses, as previous results show that retail investors react to severe shocks. Unlike retail investors, we find no evidence that institutional investors react differently to severe HCC episodes. The flow sensitivity to social performance is positive but does not vary with the level of HCC. These results suggest that the state-dependent sensitivity to social performance documented earlier is unique to retail investors.

[Insert Table 10 about here.]

7. Conclusion

We study how retail investors incorporate the social dimension of ESG into their investment decisions by developing a novel Human Capital Concern (HCC) index that captures time-varying media attention to financially material workforce-related risks. We show that retail mutual fund flows become significantly more sensitive to funds' social risk scores during periods of elevated human capital concern, with effects that are highly nonlinear and concentrated in severe and persistent episodes. In contrast, no comparable response arises when media attention focuses on ethical or values-oriented issues that are less clearly tied to firm fundamentals.

We further document that funds with stronger social performance earn higher subsequent returns following periods of elevated human capital concern. This outperformance cannot be explained by temporary demand pressure, fund-level capital movements, or managerial skill, and instead reflects a market-wide repricing of social risk that becomes salient when social concern intensify and fades as attention normalizes.

Taken together, our findings indicate that retail investors incorporate social performance into their allocation decisions when social risks become financially material. While ethical considerations may shape investment choices in normal times, they cannot account for the pronounced state dependence in capital reallocations that we document. By showing when and how the social pillar of ESG matters for retail investors, our paper contributes to the broader debate on value- versus values-driven sustainable investing and highlights that social issues, which have long been considered as the quiet pillar of ESG, can play a meaningful role in asset pricing and capital allocation when human capital risks intensify.

References

Akerlof, G.A., Kranton, R.E., 2000. Economics and identity. *Quarterly Journal of Economics* 115, 715–753.

Ammann, M., Bauer, C., Fischer, S., Müller, P., 2019. The impact of the Morningstar sustainability rating on mutual fund flows. *European Financial Management* 25, 520–553.

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

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. *Journal of Finance* 61, 1645–1680.

Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. *Quarterly Journal of Economics* 131, 1593–1636.

Barber, B.M., Huang, X., Odean, T., Schwarz, C., 2022. Attention-induced trading and returns: Evidence from robinhood users. *Journal of Finance* 77, 3141–3190.

Barber, B.M., Odean, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies* 21, 785–818.

Bauer, R., Ruof, T., Smeets, P., 2021. Get real! individuals prefer more sustainable investments. *Review of Financial Studies* 34, 3976–4043.

Bauer, R., Smeets, P., 2015. Social identification and investment decisions. *Journal of Economic Behavior & Organization* 117, 121–134.

Benson, K.L., Humphrey, J.E., 2008. Socially responsible investment funds: Investor reaction to current and past returns. *Journal of Banking & Finance* 32, 1850–1859.

Berg, F., Heeb, F., Kölbel, J., 2024. The Economic Impact of ESG Ratings. SAFE Working Paper 439. SAFE.

Berk, J.B., Green, R.C., 2004. Mutual fund flows and performance in rational markets. *Journal of Political Economy* 112, 1269–1295.

Blei, D.M., Ng, A.Y., Jordan, M.I., 2003. Latent Dirichlet Allocation. *Journal of Machine Learning Research* 3, 993–1022.

Bollen, N.P., 2007. Mutual fund attributes and investor behavior. *Journal of Financial and Quantitative Analysis* 42, 683–708.

Bonnefon, J.F., Landier, A., Sastry, P., Thesmar, D., 2025. The moral preferences of investors: Experimental evidence. *Journal of Financial Economics* 163, 103955.

Brekke, K.A., Kverndokk, S., Nyborg, K., 2003. An economic model of moral motivation. *Journal of Public Economics* 87, 1967–1983.

Campbell, J.Y., 1991. A variance decomposition for stock returns. *Economic Journal* 101, 157–179.

Campbell, J.Y., Shiller, R.J., 1988. The dividend-price ratio and expectations of future dividends and discount factors. textitReview of Financial Studies 1, 195–228. doi:`10.1093/rfs/1.3.195`.

Ceccarelli, M., Ramelli, S., Wagner, A.F., 2024. Low carbon mutual funds. *Review of Finance* 28, 45–74.

Cooper, M.J., Gulen, H., Rau, P.R., 2005. Changing names with style: Mutual fund name changes and their effects on fund flows. *Journal of Finance* 60, 2825–2858.

Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. *Journal of Finance* Introduces Google SVI as an attention measure.

De Nard, G., Engle, R.F., Kelly, B., 2024. Factor-mimicking portfolios for climate risk. *Financial Analysts Journal* 80, 37–58.

Del Guercio, D., Tkac, P.A., 2008. Star power: The effect of Morningstar ratings on mutual fund flow. *Journal of Financial and Quantitative Analysis* 43, 907–936.

Docherty, P., Hurst, G., 2018. Investor myopia and the momentum premium across international equity markets. *Journal of Financial and Quantitative Analysis* 53, 2465–2490.

Döttling, R., Kim, S., 2024. Sustainability preferences under stress: Evidence from COVID-19. *Journal of Financial and Quantitative Analysis* 59, 435–473.

Edmans, A., 2011. Does the stock market fully value intangibles? Employee satisfaction and equity prices. *Journal of Financial Economics* 101, 621–640.

Edmans, A., Pu, D., Zhang, C., Li, L., 2024. Employee satisfaction, labor market flexibility, and stock returns around the world. *Management Science* 70, 4357–4380.

Engelberg, J., McLean, R.D., Pontiff, J., 2018. Anomalies and news. *Journal of Finance* 73, 1971–2001.

Engle, R.F., Giglio, S., Kelly, B., Lee, H., Stroebel, J., 2020. Hedging climate change news. *Review of Financial Studies* 33, 1184–1216.

Faccini, R., Matin, R., Skiadopoulos, G., 2023. Dissecting climate risks: Are they reflected in stock prices? *Journal of Banking & Finance* 155, 106948.

Financial Times, 2022. Investors seek out 's' factor in esg. URL: `https://www.ft.com/content/a5e8b3f0-41a6-443d-a290-f794f7e9df93`.

Gantchev, N., Giannetti, M., Li, R., 2024. Sustainability or performance? Ratings and fund managers' incentives. *Journal of Financial Economics* 155, 103831.

Giannetti, M., Wang, T.Y., 2023. Public attention to gender equality and board gender diversity. *Journal of Financial and Quantitative Analysis* 58, 485–511.

Hartzmark, S.M., Sussman, A.B., 2019. Do investors value sustainability? A natural experiment examining ranking and fund flows. *Journal of Finance* 74, 2789–2837.

Hirshleifer, D., Teoh, S.H., 2003. Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics* 36, 337–386.

Kahneman, D., Tversky, A., 1979. Prospect theory: An analysis of decision under risk. *Econometrica* .

Khan, M., Serafeim, G., Yoon, A., 2016. Corporate sustainability: First evidence on materiality. *Accounting Review* 91, 1697–1724.

Kohlberg, L., 1981. The Philosophy of Moral Development: Moral Stages and the Idea of Justice. Harper & Row, San Francisco.

Li, Q., Watts, E.M., Zhu, C., 2024. Retail investors and esg news. *Journal of Accounting and Economics* 78, 101719.

Mayr, U., Freund, A.M., 2020. Do we become more prosocial as we age, and if so, why? *Current Directions in Psychological Science* 29, 248–254.

McCombs, M.E., Shaw, D.L., 1972. The agenda-setting function of mass media. *Public Opinion Quarterly* 36, 176–187.

Nimark, K.P., Pitschner, S., 2019. News media and delegated information choice. *Journal of Economic Theory* 181, 160–196.

Pastor, L., Stambaugh, R.F., Taylor, L.A., 2022. Dissecting green returns. *Journal of Financial Economics* 146, 403–424.

Pastor, L., Vorsatz, M.B., 2020. Mutual fund performance and flows during the COVID-19 crisis. *Review of Asset Pricing Studies* 10, 791–833.

Pedersen, L.H., Fitzgibbons, S., Pomorski, L., 2021. Responsible investing: The esg-efficient frontier. *Journal of Financial Economics* 142, 572–597.

Pennebaker, J.W., Boyd, R.L., Jordan, K., Blackburn, K., 2015. The development and psychometric properties of LIWC2015. *Technical Report, University of Texas at Austin.* .

Peress, J., 2014. The media and the diffusion of information in financial markets: Evidence from newspaper strikes. *Journal of Finance* 69, 2007–2043.

Pons, P., Latapy, M., 2006. Computing communities in large networks using random walks. *Journal of Graph Algorithms and Applications* 10, 191–218.

Riedl, A., Smeets, P., 2017. Why do investors hold socially responsible mutual funds? *Journal of Finance* 72, 2505–2550.

Roberts, M.E., Stewart, B.M., Tingley, D., 2019. STM: An R package for structural topic models. *Journal of Statistical Software* 91, 1–40.

Rossi, M., Sansone, D., Van Soest, A., Torricelli, C., 2019. Household preferences for socially responsible investments. *Journal of Banking & Finance* 105, 107–120.

Sautner, Z., van Lent, L., Vilkov, G., Zhang, R., 2023. Firm-level climate change exposure. *Journal of Finance* 78, 1449–1498.

Shan, C., Tang, D.Y., 2023. The value of employee satisfaction in disastrous times: Evidence from COVID-19. *Review of Finance* 27, 1027–1076.

Shefrin, H., Statman, M., 2000. Behavioral portfolio theory. *Journal of Financial and Quantitative Analysis* 35, 127–151.

Sloan, R.G., 2024. Retail investors and ESG news: A discussion. *Journal of Accounting and Economics* 78, 101730.

Starks, L.T., 2023. Presidential address: Sustainable finance and esg issues—value versus values. *Journal of Finance* 78, 1837–1872.

Teo, M., Woo, S.J., 2004. Style effects in the cross-section of stock returns. *Journal of Financial Economics* 74, 367–398.

Table 1: Sources of human capital news
This table reports the number and the percentage of articles discussing "work and staff" topics from January 2010 to June 2024. The table also reports the average concern, sentiment and risk score as well as the percentage of time a score is zero.

	Articles		Concern Score		Sentiment Score		Risk Score	
	N	%	Mean	0%	Mean	0%	Mean	0%
NYT	5,981	0.70	0.356	5.85	0.452	0.85	0.719	5.50
WSJ	10,165	2.17	0.309	12.20	0.401	2.95	0.679	10.89

Table 2: Summary statistics of fund characteristics

This table reports the summary statistics for monthly percentage net flows, assets under management (TNA, in millions of dollars), the age of the fund (in months), the monthly returns, the fund's Morningstar star rating, and the fund's environmental and social risk scores provided by Morningstar. The sample includes all U.S.-domiciled equity funds with an ESG score and ranges from January 2015 to May 2023.

Variable	N	Mean	Std dev	Min	1st Qu.	Median	3rd Qu.	Max
Panel A: Fund characteristics for retail and institutional funds								
Net Flow (%)	474,297	-0.21	6.83	-37.20	-1.59	-0.53	0.47	104.00
Monthly return (%)	474,297	0.58	5.07	-39.90	-2.18	0.89	3.45	34.90
Star rating	474,297	3.13	1.00	1.00	2.50	3.00	4.00	5.00
Age (month)	474,297	195.00	134.00	2.00	96.00	172.00	261.00	1,190.00
TNA (million USD)	474,297	1,930.00	13,600.00	0.00	43.33	213.52	895.67	1,000,000.00
Panel B: Fund characteristics for retail funds								
Net Flow (%)	263,519	-0.44	6.16	-37.20	-1.57	-0.66	0.17	104.00
Monthly return (%)	263,519	0.58	5.06	-39.90	-2.18	0.88	3.43	34.90
Star rating	263,519	3.04	0.97	1.00	2.33	3.00	3.86	5.00
Age (month)	263,519	223.00	151.00	2.00	113.00	205.00	289.00	1,190.00
TNA (million USD)	263,519	1,950.00	9,670.00	0.00	52.07	253.00	1,050.00	399,000.00
Panel C: Fund characteristics for institutional funds								
Net Flow (%)	210,778	0.08	7.58	-37.20	-1.63	-0.31	0.90	104.00
Monthly return (%)	210,778	0.59	5.05	-39.90	-2.19	0.90	3.47	34.09
Star rating	210,778	3.25	1.03	1.00	3.00	3.00	4.00	5.00
Age (month)	210,778	160.00	98.40	2.00	83.00	140.00	221.00	1,140.00
TNA (million USD)	210,778	1,910.00	17,400.00	0.00	36.14	172.00	727.81	1,000,000.00

Table 3: Summary statistics of Morningstar sustainability scores

This table reports the distributions of social (*Soc*), environmental (*Env*), and aggregate ESG (*ESG*) scores before the methodology change in September 2019, after the methodology change and the variables ranked in percentiles to allow comparability before/after the methodology change. The sample includes all U.S.-domiciled equity funds with an ESG score and ranges from January 2015 to May 2023.

Variable	N	Mean	Std dev	Min	1st Qu.	Median	3rd Qu.	Max
Panel A: ESG Scores – Before September 2019								
Soc	254,321	50.90	4.23	39.30	47.80	51.30	53.80	61.60
Env	254,321	52.00	5.14	37.20	48.70	53.10	55.80	62.70
ESG	254,321	46.20	3.79	37.10	44.00	46.20	48.60	57.50
Panel B: ESG Scores – After September 2019								
Soc	219,976	8.49	2.57	0.22	7.88	9.21	10.10	13.80
Env	219,976	4.18	2.03	0.13	3.03	4.04	5.06	15.90
ESG	219,976	23.20	3.19	13.10	21.40	23.00	24.90	39.30
Panel C: ESG Scores – Percentile ranked								
Soc	474,297	0.50	0.29	0.00	0.25	0.50	0.75	1.00
Env	474,297	0.51	0.29	0.00	0.26	0.51	0.76	1.00
ESG	474,297	0.51	0.28	0.00	0.28	0.52	0.75	1.00

Table 4: Flow-performance sensitivity along social concern

This table reports the results of regression analyzing the flow-performance sensitivity in times of social concern. The environmental (*Env*) and social (*Soc*) scores are ranked in percentiles to allow comparability before/after the methodology change that occurred in 2019. All variables are standardized by subtracting their time-series mean and dividing them by their time-series standard deviation. Standard errors are clustered at the fund level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Dependent variable: Net Flow (%)				
	(1)	(2)	(3)	(4)	(5)
Return_{t-1}	0.355***	0.361***	0.353***	0.352***	0.361***
	(0.025)	(0.026)	(0.026)	(0.026)	(0.027)
Star_{t-1}	0.694***	0.695***	0.689***	0.690***	0.709***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)
Log(Age)_{t-1}	-0.296***	-0.302***	-0.303***	-0.304***	-0.307***
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Log(Size)_{t-1}	-0.416***	-0.411***	-0.416***	-0.417***	-0.418***
	(0.032)	(0.033)	(0.032)	(0.033)	(0.032)
Flow_{t-1} (%)	1.330***	1.336***	1.322***	1.322***	1.321***
	(0.098)	(0.098)	(0.098)	(0.098)	(0.097)
Env_{t-1}	-0.063***	-0.028*	-0.063***	-0.078***	-0.089***
	(0.023)	(0.021)	(0.026)	(0.026)	(0.030)
Soc_{t-1}	0.071***	0.059***	0.048***	0.073***	0.078***
	(0.021)	(0.020)	(0.025)	(0.028)	(0.029)
$\text{HCC}_{t-1} \times \text{Soc}_{t-1}$	0.024*	0.031**	0.026	0.042**	0.047**
	(0.014)	(0.014)	(0.018)	(0.019)	(0.021)
$\text{HCC}_{t-1} \times \text{Return}_{t-1}$					0.019
					(0.019)
$\text{HCC}_{t-1} \times \text{Star}_{t-1}$					0.129***
					(0.018)
$\text{HCC}_{t-1} \times \text{Env}_{t-1}$					0.002
					(0.021)
Observations	263,519	263,519	263,519	263,519	263,519
Funds	3,915	3,915	3,915	3,915	3,915
Style FE	Yes	No	No	No	No
Time FE	No	Yes	No	No	No
Style × Time FE	No	No	Yes	Yes	Yes
COVID	No	No	No	Yes	Yes
R^2	0.047	0.052	0.057	0.057	0.058
Adjusted R^2	0.047	0.052	0.054	0.054	0.054

Table 5: Shock intensity

This table reports the results of regression analyzing the flow-performance sensitivity in times of social concern given several intensity thresholds. We standardize the *Index* by subtracting its time-series mean and dividing it by its time-series standard deviation. The intensity thresholds are defined as follows: *Very low HCC* when the index value is more than one standard deviation below the average, *Low HCC* when the index value is between one standard deviation below the average and the average, *Moderate HCC* when the index value is between the average and one standard deviation above the average, and *Severe HCC* when the index value is higher than one standard deviation above the average. The reference category is when *HCC* is below average. Standard errors are clustered at the fund level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Net flow (%)		
	(1)	(2)	(3)
Return_{t-1}	0.360***	0.360***	0.358***
	(0.026)	(0.026)	(0.026)
Star_{t-1}	0.700***	0.697***	0.692***
	(0.025)	(0.025)	(0.025)
Log(Age)_{t-1}	-0.301***	-0.302***	-0.304***
	(0.035)	(0.035)	(0.035)
Log(Size)_{t-1}	-0.411***	-0.411***	-0.416***
	(0.033)	(0.033)	(0.033)
Flow_{t-1} (%)	1.334***	1.248***	1.236***
	(0.098)	(0.098)	(0.098)
Env_{t-1}	-0.050**	-0.053**	-0.088***
	(0.023)	(0.022)	(0.027)
Soc_{t-1}	0.056**	0.060***	0.061**
	(0.023)	(0.023)	(0.029)
Moderate $\text{HCC}_{t-1} \times \text{Soc}_{t-1}$	0.020	0.019	-0.008
	(0.029)	(0.029)	(0.037)
Severe $\text{HCC}_{t-1} \times \text{Soc}_{t-1}$	0.118***	0.114***	0.120**
	(0.040)	(0.040)	(0.053)
Observations	263,519	263,519	263,519
Funds	3,915	3,915	3,915
COVID	Yes	Yes	Yes
Style FE	Yes	No	No
Time FE	No	Yes	No
Style × Time FE	No	No	Yes
R^2	0.047	0.052	0.057
Adjusted R^2	0.047	0.052	0.054

Table 6: Shock duration

This table reports regression results analyzing the impact of social and ESG dimensions on mutual fund flows, and the divergence in reaction between long versus short shocks. A *Short Shock* is a month during which the value of the HCC index reaches the defined range and returns below the range in the following month. Long shocks (*Long Shock*) are months when the HCC index value reaches the defined range and remains within it for more than one period. The intensity ranges of the shock correspond to Low, Moderate, Severe. All variables are standardized. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Net Flow (%)		
	Low	Moderate	Severe
	(1)	(2)	(3)
Return_{t-1}	0.359***	0.358***	0.358***
	(0.014)	(0.014)	(0.014)
Star_{t-1}	0.691***	0.692***	0.692***
	(0.014)	(0.014)	(0.014)
Log(Age)_{t-1}	-0.304***	-0.304***	-0.304***
	(0.022)	(0.022)	(0.022)
Log(Size)_{t-1}	-0.415***	-0.415***	-0.416***
	(0.016)	(0.016)	(0.016)
Flow_{t-1} (%)	1.322***	1.322***	1.322***
	(0.017)	(0.017)	(0.017)
Env_{t-1}	-0.080***	-0.082***	-0.088***
	(0.018)	(0.018)	(0.018)
Soc_{t-1}	0.074***	0.086***	0.059***
	(0.021)	(0.021)	(0.019)
Long Shock × Soc_{t-1}	0.004	-0.029	0.154***
	(0.035)	(0.033)	(0.047)
Short Shock × Soc_{t-1}	-0.355***	-0.331**	-0.006
	(0.162)	(0.163)	(0.091)
Observations	263,519	263,519	263,519
Funds	3,915	3,915	3,915
Style × Time FE	Yes	Yes	Yes
R^2	0.057	0.57	0.057
Adjusted R^2	0.054	0.054	0.054
Residual Std. Error	5.995	5.995	5.995
F Statistic	17.660***	17.660***	17.667***

Table 7: Return predictability
This table reports regression results for fund returns at horizons t to $t+4$. The dependent variable is the fund return at each horizon. Standard errors are clustered at the fund level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Return				
	Return_t	Return_{t+1}	Return_{t+2}	Return_{t+3}	Return_{t+4}
Star_{t-1}	0.163***	0.007	0.011**	0.009*	0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$\text{Log}(\text{Age}_{t-1})$	0.105***	0.061***	0.063***	0.058***	0.061***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$\text{Log}(\text{Size}_{t-1})$	-0.31***	0.030***	0.030***	0.028***	0.031***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Flow_{t-1}	-0.021***	0.001	-0.002	-0.007	0.006
	(0.006)	(0.008)	(0.007)	(0.007)	(0.007)
Soc_{t-1}	-0.026***	-0.007	-0.007	-0.101***	-0.121***
	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
Env_{t-1}	-0.005	-0.024***	-0.027***	0.072***	0.069***
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)
$\text{HCC}_{t-1} \times \text{Soc}_{t-1}$	0.047***	0.091***	0.083***	0.008	-0.001
	(0.008)	(0.008)	(0.009)	(0.006)	(0.006)
$\text{HCC}_{t-1} \times \text{Env}_{t-1}$	-0.020**	-0.111***	-0.118***	0.034***	0.040***
	(0.009)	(0.010)	(0.009)	(0.007)	(0.007)
Observations	263,519	259,667	255,831	252,024	248,234
Funds	3,915	3,896	3,865	3,843	3,824
Style × Time FE	Yes	Yes	Yes	Yes	Yes
Covid	Yes	Yes	Yes	Yes	Yes
R^2	0.822	0.821	0.822	0.822	0.823
Adjusted R^2	0.821	0.820	0.822	0.821	0.822

Table 8: Results of causal mediation analysis
This table reports the results of a causal mediation analysis examining the indirect effect of social score on fund returns through fund flows as the mediator. The table reports the estimates, 95% confidence intervals, and p-values for the Average Causal Mediation Effect (ACME), Average Direct Effect (ADE), Total Effect, and Proportion Mediated. Estimates are based on nonparametric bootstrap confidence intervals (percentile method) using 1,000 simulations and a sample size of 351,357. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Effect	Estimate	CI Lower	CI Upper	P-value
ACME (Indirect)	0.000868	0.000206	0.001497	0.008
ADE (Direct)	0.033866	0.018374	0.050708	0.000
Total Effect	0.034734	0.018580	0.052205	0.000

Table 9: Performance of passive investment funds
This table reports regression results for fund returns at horizons t to $t+4$. The dependent variable is the fund return at each horizon. Panel A provides the results for the index fund asset class. Panel B focuses on exchange-traded funds. Standard errors are clustered at the fund level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Index Funds

	Dependent variable: Return				
	Return_t	Return_{t+1}	Return_{t+2}	Return_{t+3}	Return_{t+4}
Soc_{t-1}	0.062***	0.065***	0.055***	-0.002	-0.048***
	(0.015)	(0.016)	(0.015)	(0.013)	(0.015)
$\text{HCC}_{t-1} \times \text{Soc}_{t-1}$	0.055***	0.081***	0.038**	0.030**	-0.007
	(0.015)	(0.017)	(0.016)	(0.013)	(0.013)
Observations	98,169	96,661	95,160	93,675	92,194
Funds	1,295	1,286	1,275	1,271	1,267
Controls	Yes	Yes	Yes	Yes	Yes
Style × Time FE	Yes	Yes	Yes	Yes	Yes
COVID-19	Yes	Yes	Yes	Yes	Yes
R^2	0.787	0.787	0.789	0.789	0.789
Adjusted R^2	0.785	0.785	0.787	0.787	0.787

Panel B: Exchange-Traded Funds

	Dependent variable: Return				
	Return_t	Return_{t+1}	Return_{t+2}	Return_{t+3}	Return_{t+4}
Soc_{t-1}	0.088***	0.095***	0.081***	0.031**	-0.013
	(0.018)	(0.017)	(0.017)	(0.015)	(0.017)
$\text{HCC}_{t-1} \times \text{Soc}_{t-1}$	0.062***	0.070***	0.031*	0.025*	-0.010
	(0.018)	(0.019)	(0.017)	(0.015)	(0.014)
Observations	68,966	67,757	66,566	65,391	64,225
Funds	1,213	1,194	1,180	1,171	1,158
Controls	Yes	Yes	Yes	Yes	Yes
Style × Time FE	Yes	Yes	Yes	Yes	Yes
COVID-19	Yes	Yes	Yes	Yes	Yes
R^2	0.747	0.746	0.748	0.748	0.748
Adjusted R^2	0.743	0.743	0.744	0.745	0.745

Table 10: Flow-social performance sensitivity of institutional investors
This table reports the results of regression analysis of the flow-performance sensitivity in times of social concern. The environmental (*Env*) and social (*Soc*) scores are ranked in percentiles to allow comparability before/after the methodology change that occurred in 2019. All variables are standardized by subtracting their time-series mean and dividing them by their time-series standard deviation. Standard errors are clustered at the fund level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Dependent variable: Net flow (%)	
	(1)	(2)
Return_{t-1}	0.307***	0.307***
	(0.028)	(0.028)
Star_{t-1}	1.067***	1.043***
	(0.029)	(0.028)
Log(Age)_{t-1}	-0.530***	-0.526***
	(0.045)	(0.045)
Log(Size)_{t-1}	-0.786***	-0.785***
	(0.036)	(0.036)
Flow_{t-1} (%)	1.804***	1.805***
	(0.051)	(0.051)
Env_{t-1}	-0.104***	-0.129***
	(0.036)	(0.033)
Soc_{t-1}	0.142***	0.103***
	(0.035)	(0.034)
$\text{HCC}_{t-1} \times \text{Soc}_{t-1}$	0.035	
	(0.026)	
Moderate HCC $\times$ Soc_{t-1}		0.101*
		(0.052)
Severe HCC $\times$ Soc_{t-1}		0.131*
		(0.074)
Observations	210,778	210,778
Funds	3,288	3,288
Style x Time FE	Yes	Yes
COVID	Yes	Yes
R^2	0.097	0.096
Adjusted R^2	0.093	0.092

Table 11: Flow-social performance sensitivity along Human Rights and Individual Freedom concern
This table reports the results of regression analyzing the flow-performance sensitivity in times of social concern as measured by Human Rights and Individual Freedom Concern index. All variables are standardized by subtracting their time-series mean and dividing them by their time-series standard deviation. Standard errors are clustered at the fund level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Dependent variable: Net flow (%)			
	(1)	(2)	(3)	(4)
Return_{t-1}	0.354***	0.360***	0.353***	0.358***
	(0.025)	(0.025)	(0.026)	(0.026)
Star_{t-1}	0.693***	0.694***	0.689***	0.691***
	(0.024)	(0.024)	(0.024)	(0.025)
Log(Age)_{t-1}	-0.296***	-0.302***	-0.304***	-0.305***
	(0.035)	(0.035)	(0.035)	(0.035)
Log(Size)_{t-1}	-0.413***	-0.409***	-0.415***	-0.415***
	(0.032)	(0.033)	(0.033)	(0.032)
Flow_{t-1} (%)	1.330***	1.337***	1.322***	1.322***
	(0.097)	(0.098)	(0.098)	(0.098)
Env_{t-1}	-0.067***	-0.029*	-0.063***	-0.83***
	(0.023)	(0.022)	(0.026)	(0.027)
Soc_{t-1}	0.072***	0.059***	0.050***	0.074***
	(0.021)	(0.020)	(0.026)	(0.027)
$\text{HRC}_{t-1} \times \text{Soc}_{t-1}$	0.015	0.020	0.014	0.005
	(0.014)	(0.014)	(0.017)	(0.017)
$\text{HRC}_{t-1} \times \text{Return}_{t-1}$	0.019	0.012	0.013	0.010
	(0.017)	(0.017)	(0.019)	(0.018)
$\text{HRC}_{t-1} \times \text{Star}_{t-1}$	0.006	0.006	0.006	0.005
	(0.015)	(0.015)	(0.015)	(0.015)
$\text{HRC}_{t-1} \times \text{Env}_{t-1}$	-0.023*	-0.020	-0.020	-0.015
	(0.014)	(0.014)	(0.019)	(0.018)
Observations	263,519	263,519	263,519	263,519
Funds	3,195	3,195	3,195	3,195
Style FE	Yes	No	No	No
Time FE	No	Yes	No	No
Style x Time FE	No	No	Yes	Yes
COVID	No	No	No	Yes
R^2	0.047	0.052	0.057	0.057
Adjusted R^2	0.047	0.052	0.054	0.054

Table 12: Social Risk Score versus ESG Name

This table reports the results of regression analysis of the flow-performance sensitivity in times of social concern. The environmental (*Env*) and social (*Soc*) scores are ranked in percentiles to allow comparability before/after the methodology change that occurred in 2019. *ESG Name* is a dummy variable equal to 1 if the fund name includes sustainability-related terms and 0 otherwise. All variables are standardized by subtracting their time-series mean and dividing them by their time-series standard deviation. Standard errors are clustered at the fund level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Dependent variable: Net Flow		
	(1)	(2)	(3)
Return_{t-1}	0.353***	0.351***	0.351***
	(0.026)	(0.026)	(0.026)
Star_{t-1}	0.688***	0.689***	0.689***
	(0.024)	(0.024)	(0.024)
Log(Age)_{t-1}	-0.301***	-0.301***	-0.301***
	(0.035)	(0.035)	(0.035)
Log(Size)_{t-1}	-0.412***	-0.414***	-0.414***
	(0.033)	(0.033)	(0.033)
Flow_{t-1} (%)	1.321***	1.320***	1.320***
	(0.098)	(0.098)	(0.098)
Soc_{t-1}	0.043**	0.072***	0.070***
	(0.025)	(0.029)	(0.029)
Env_{t-1}	-0.061***	-0.088***	-0.088***
	(0.026)	(0.030)	(0.030)
ESG_Name	0.224*	0.220*	0.173
	(0.120)	(0.120)	(0.126)
HCC_{t-1} × ESG_Name	-0.173**	-0.188**	-0.177**
	(0.077)	(0.077)	(0.082)
$\text{HCC}_{t-1} \times \text{Soc}_{t-1}$		0.044**	0.045**
		(0.021)	(0.021)
$\text{HCC}_{t-1} \times \text{Env}_{t-1}$		0.010	0.010
		(0.021)	(0.021)
Soc_{t-1} × ESG_Name			0.132
			(0.154)
Soc_{t-1} × ESG_Name × HCC_{t-1}			-0.042
			(0.120)
Observations	263,519	263,519	263,519
Funds	3,195	3,195	3,195
Style x Time FE	Yes	Yes	Yes
COVID	Yes	Yes	Yes
R^2	0.057	0.057	0.057
Adjusted R^2	0.054	0.054	0.054
Residual Std. Error	5.995	5.995	5.995
F Statistic	17.712***	17.661***	17.624***

Figure 1: Monthly Human Capital Concern index
This figure displays the monthly HCC index. The plot starts in 2015 and ends in June 2023. For ease of interpretation, we standardize the index by subtracting its mean and then dividing by its standard deviation so that 1 on the y-axis means one standard deviation above the mean.

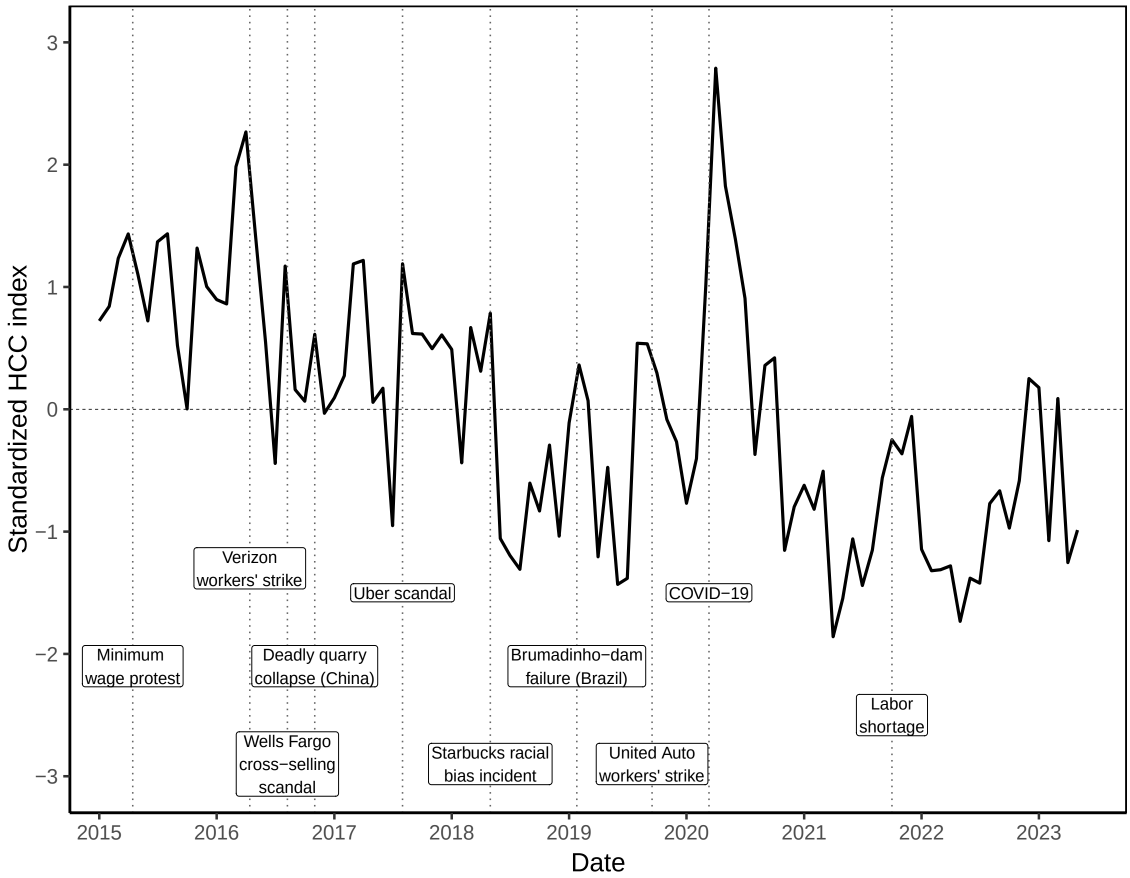


Figure 2: Flow-performance sensitivity per terciles of HCC
This figure displays the average values of the flow-performance sensitivity of retail investors, along with 95% confidence intervals, by terciles of Human Capital Concern. The flow-performance sensitivity is the slope from monthly cross-sectional regressions of fund flows on lagged sustainability performance measures. The range goes from January 2015 to May 2023.

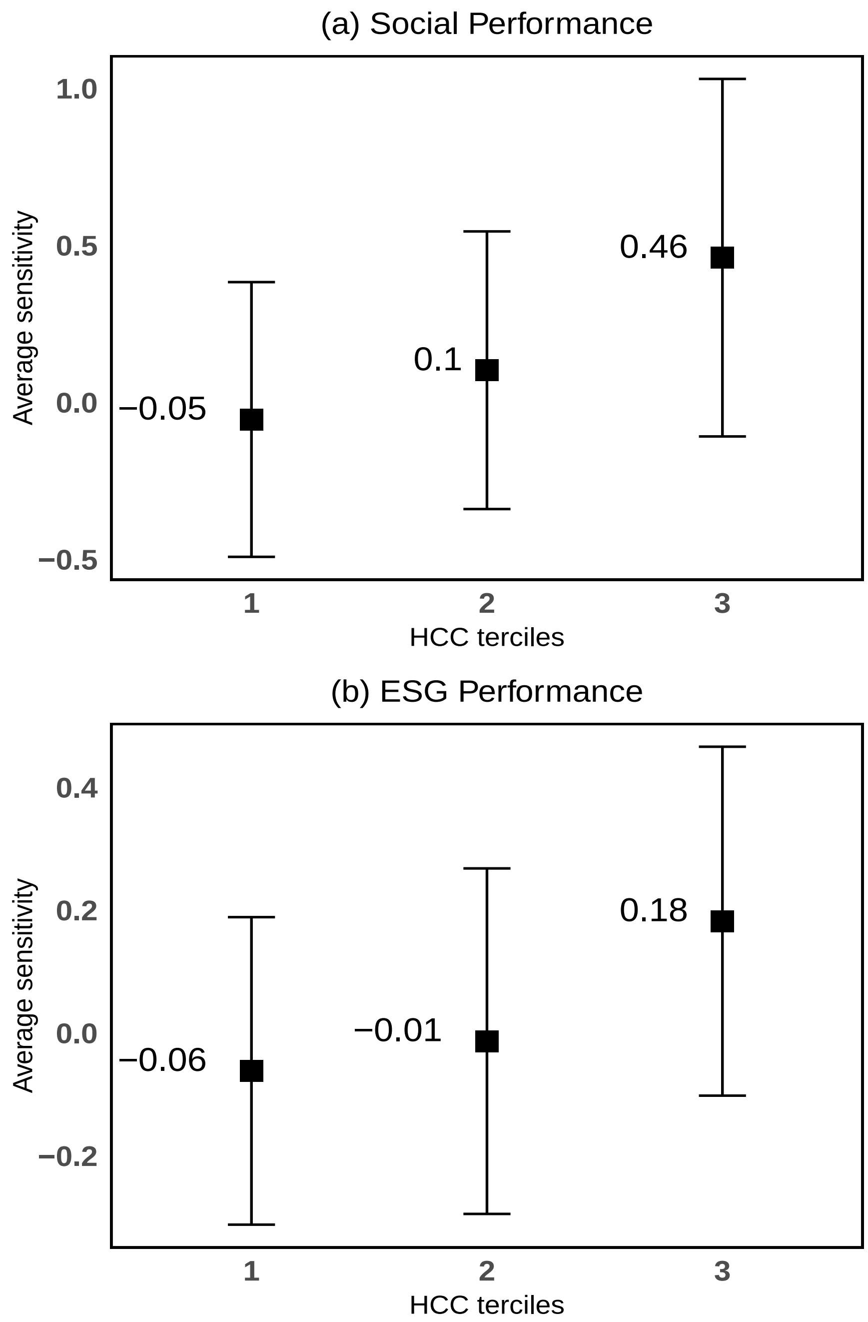
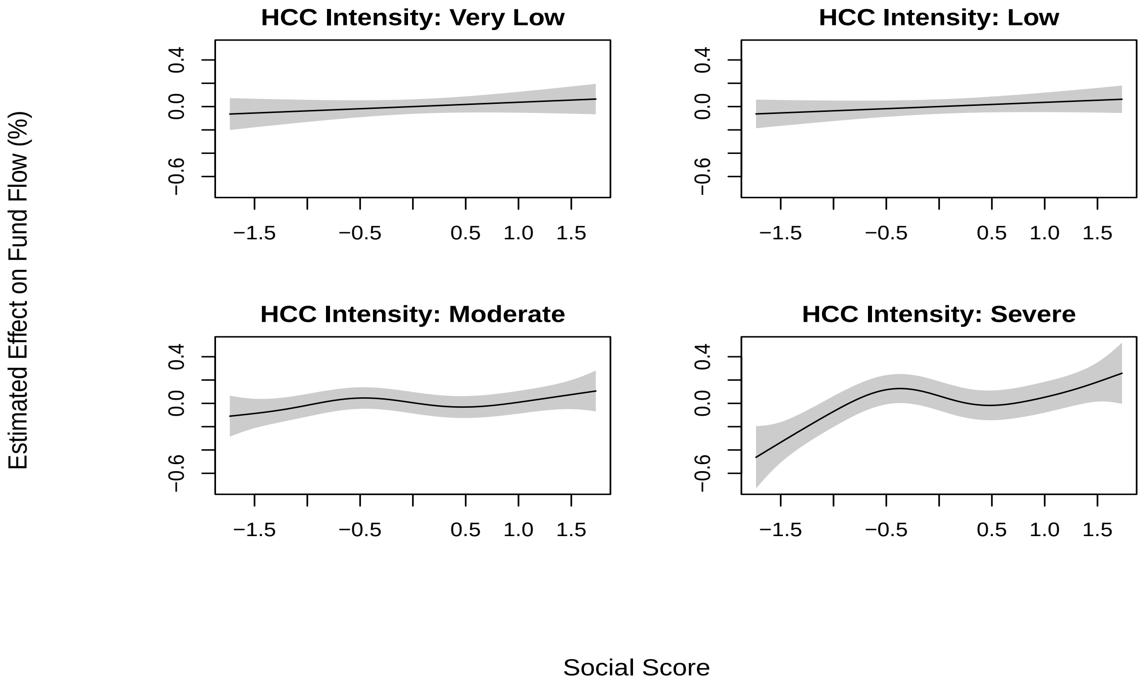


Figure 3: Generalized Additive Model regression - HCC intensity
The figure displays the estimated smooth effects of social score on fund net flows across four groups defined by varying levels of Human Capital Concern intensity, with 95% confidence intervals.



Appendix A. Variable Definitions

Variable	Definition
$Flow_{i,t}$	Monthly net percentage flow of fund i in month t, computed as $\frac{TNA_{i,t}}{TNA_{i,t-1}} - (1 + R_{i,t})$. Winsorized at the 1st and 99th percentiles.
$Return_{i,t}$	Monthly total return of fund i. Winsorized at the 1st and 99th percentiles.
$TNA_{i,t}$	Total net assets under management (USD). Log-transformed in regressions.
$Age_{i,t}$	Fund age in months since inception of the oldest share class. Log-transformed in regressions.
$Star_{i,t}$	Morningstar star rating (1–5), treated as continuous.
$Soc_{i,t}$	Portfolio-level social score equal to the asset-weighted average of Sustainalytics firm-level social risk scores. Converted into monthly percentile ranks.
$Env_{i,t}$	Portfolio-level environmental score constructed analogously to $Soc_{i,t}$. Converted into monthly percentile ranks.
$ESG_{i,t}$	Portfolio-level aggregate ESG score constructed analogously to $Soc_{i,t}$. Converted into monthly percentile ranks.
HCC_t	Human Capital Concern index capturing media attention to financially material human capital risks. Constructed from articles published in *The Wall Street Journal* and *The New York Times* using risk and sentiment lexicons (LIWC-22). The daily index is aggregated to a monthly frequency and standardized.
HRC_t	Human Rights Concern index constructed analogously to HCC_t using articles classified under human rights and individual freedoms.
$COVID_t$	Indicator variable equal to one from January 2020 to July 2020, and zero otherwise.
$Severe_t$, $Moderate_t$, Low_t, $VeryLow_t$	Indicator variables based on the level of HCC_t relative to its full-sample mean and standard deviation: $Severe_t = 1$ if $HCC_t > +1$ SD; $Moderate_t = 1$ if mean $< HCC_t \leq +1$ SD; $Low_t = 1$ if -1 SD $\leq HCC_t \leq$ mean; $VeryLow_t = 1$ if $HCC_t < -1$ SD.
$ShortShock_t$	Indicator equal to one if HCC_t ranges within a given intensity range for only one month.
$LongShock_t$	Indicator equal to one if HCC_t remains within a given intensity range for at least two consecutive months.
$ESGName_{i,t}$	Indicator equal to one if the fund's legal name contains ESG-related keywords, and zero otherwise. Matching is performed using case-insensitive regular expressions.

Notes: All explanatory variables are standardized (mean zero, unit variance) prior to estimation unless otherwise stated. Sustainability scores are percentile-ranked each month to ensure consistency before and after the Sustainalytics methodology revision reflected in September 2019 in Morningstar Direct database. Higher values of *Soc*, *Env*, and *ESG* indicate stronger sustainability performance (lower unmanaged ESG risk).

Appendix B. Orthogonality of HCC to macroeconomic variables

To assess whether HCC captures idiosyncratic social attention rather than general economic or financial stress, we perform a regression of monthly changes in HCC on contemporaneous changes in several well-established macroeconomic indicators. Specifically, we include the unemployment rate, market volatility (VIX), consumer price index (CPI), the Economic Policy Uncertainty (EPU) index, and the Media Climate Change Concern (MCCC) index.[16] This analysis tests the orthogonality of HCC with respect to broad macroeconomic conditions: if HCC were largely driven by general economic stress, we would expect significant coefficients and a substantial R^2.

Table B.13: Regression of monthly changes in HCC on macro variables

Variable	Coefficient	Std. Error	t-statistic	p-value
Intercept	-0.004	0.0155	-0.288	0.774
Δ Unemployment Rate	0.043	0.0195	2.22	0.029
Δ VIX	0.005	0.0039	1.29	0.200
Δ CPI	-0.003	0.0452	-0.068	0.946
Δ EPU	0.000	0.001	0.145	0.885
Δ MCCC	0.049	0.043	1.140	0.256
R^2		0.117		
Adjusted-R^2		0.071		
Observations		N = 101		

The regression results indicate that the model only explains about 11.7% of the monthly variation in HCC ($R^2 = 0.117$). All coefficients, except for the unemployment rate, are statistically insignificant and economically negligible. Even the unemployment coefficient, while marginally significant, has a very small economic magnitude, implying that a 1 percentage point change in unemployment corresponds to only a 0.043 change in HCC. These results suggest that HCC is largely independent of macroeconomic fluctuations and therefore captures attention-driven dynamics and social concern rather than aggregate economic conditions. Establishing this orthogonality provides robustness for interpreting HCC as a measure of idiosyncratic investor attention and social concern, rather than a proxy for macroeconomic stress.

[16] All macroeconomic variables (UNRATE, VIXCLS, CPALTT01USM657N, and USEPUINDXD) are retrieved from `https://fred.stlouisfed.org/`. MCCC variable is retrieved from `https://sentometrics-research.com/download/mccc/`.

Appendix C. The role of media in measuring attention to ESG factors

Media plays a crucial role in shaping decision-making processes across various domains, including public opinion and financial behavior. The "agenda-setting" capability of media, as described by McCombs and Shaw (1972), highlights its ability to influence the importance individuals assign to specific issues, thereby guiding the public's focus toward certain topics. The media also serves as an essential information intermediary, bridging the gap between consumers, investors, and the broader state of the world (Nimark and Pitschner, 2019). This intermediary role is particularly significant in the financial sector, where media coverage can directly impact investor behavior by influencing the attention they allocate to particular stocks or market trends (Barber and Odean, 2008). Media does not only convey information but also actively shapes the decisions and actions of individuals, including investors, who rely on it to navigate complex economic landscapes. In addition, news framing influences people's attitudes and evaluations regarding specific topics. The media editorial board can therefore significantly influence individual behavior as its orientation plays a significant role in shaping narratives on social and political issues by influencing both the selection of topics covered and the perspectives from which they are presented. Engelberg et al. (2018) further explore how news coverage influences investor behavior, demonstrating that media coverage plays a crucial role in correcting market anomalies by driving stock prices toward their true value and reducing mispricing in response to news about specific stocks or economic events.

While a growing literature develops indices to measure attention to ESG dimensions, most of them focus on the environmental aspect of ESG. Engle et al. (2020) construct a climate risk index by analyzing the similarity between Wall Street Journal articles and climate-related texts, showing how climate risk exposure can be hedged through mimicking portfolios. Ardia et al. (2023) expand this approach by incorporating a wider range of news sources, building a lexicon-based climate concern index that links climate-related sentiment to stock performance. Sautner et al. (2023) apply textual analysis to corporate earnings calls to assess climate risk exposure. Faccini et al. (2023) use textual and narrative analysis of Reuters climate change news to distinguish between physical and transition climate risks. Turning to the social dimension, Giannetti and Wang (2023) use Google Search Trends to construct an index measuring public attention to gender equality.

Appendix D. COVID-19 period - Full Table

Table D.14: Flow-performance sensitivity and COVID-sensitive contexts
This table reports regression results analyzing the impact of social and ESG dimensions on mutual fund flows, interacting ESG scores with both the HCC index and the COVID-19 period dummy. All variables are standardized. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Net Flow (%)			
	(1)	(2)	(3)	(4)
Return_{t-1}	0.354***	0.361***	0.378***	0.378***
	(0.014)	(0.015)	(0.014)	(0.014)
Star_{t-1}	0.698***	0.709***	0.701***	0.712***
	(0.013)	(0.014)	(0.013)	(0.014)
Log(Age)_{t-1}	-0.306***	-0.307***	-0.300***	-0.300***
	(0.022)	(0.022)	(0.022)	(0.022)
Log(Size)_{t-1}	-0.417***	-0.418***	-0.427***	-0.427***
	(0.016)	(0.016)	(0.015)	(0.015)
Flow_{t-1} (%)	1.321***	1.321***	1.351***	1.351***
	(0.017)	(0.017)	(0.016)	(0.016)
Env_{t-1}	-0.058***	-0.089***		
	(0.017)	(0.019)		
Soc_{t-1}	0.043**	0.078***		
	(0.017)	(0.019)		
ESG_{t-1}			-0.002	0.005
			(0.015)	(0.015)
$\text{HCC}_{t-1} \times \text{Return}_{t-1}$	0.013	0.019	0.013	0.011
	(0.014)	(0.015)	(0.014)	(0.015)
$\text{HCC}_{t-1} \times \text{Star}_{t-1}$	0.121***	0.129***	0.109***	0.118***
	(0.013)	(0.013)	(0.013)	(0.013)
$\text{HCC}_{t-1} \times \text{Env}_{t-1}$	0.029*	0.002		
	(0.017)	(0.018)		
$\text{HCC}_{t-1} \times \text{Soc}_{t-1}$	0.018**	0.047***		
	(0.017)	(0.018)		
$\text{HCC}_{t-1} \times \text{ESG}_{t-1}$			0.035**	0.040***
			(0.015)	(0.015)
$\text{Return}_{t-1} \times \text{COVID}_t$		-0.132***		0.020
		(0.065)		(0.057)
$\text{Star}_{t-1} \times \text{COVID}_t$		-0.151***		-0.147***
		(0.055)		(0.049)
$\text{Env}_{t-1} \times \text{COVID}_t$		0.137**		
		(0.063)		
$\text{Soc}_{t-1} \times \text{COVID}_t$		-0.228***		
		(0.059)		
$\text{ESG}_{t-1} \times \text{COVID}_t$				-0.080
				(0.057)
Observations	263,519	263,519	274,196	274,196
Style × Time FE	Yes	Yes	Yes	Yes
R^2	0.058	0.058	0.059	0.059
Adjusted R^2	0.054	0.054	0.056	0.056
Residual Std. Error	5.994	5.994	6.046	6.046
F Statistic	17.788***	17.744***	18.953***	18.903***

During the pandemic, the relationship exhibits a notable reversal: funds with strong social performance attracted fewer flows, while environmental funds received increased capital. One possible explanation of the reversal of these relationships between flow sensitivity to sustainability performance and the level of concern in times of market crisis is a change in investor preferences under uncertainty. As Ardia et al. (2023) show in the update of their MCCC index (see `https://sentometrics-research.com/post/2023-climate-change/`), concern about climate change decreases during this time, while our social concern index rises sharply. However, as Pastor and Vorsatz (2020) document, funds with an environmental focus outperformed and attracted more capital during the crisis, whereas funds exhibiting good social performance underperformed and attracted fewer flows than low-rated funds.

Appendix E. Correlation matrix

Table E.15: Correlation matrix of financial and non-financial performance measures

	Env. score	Soc. score	Return	Star rating
Env. score	1.0000			
Soc. score	0.5853	1.0000		
Return	0.0142	-0.0189	1.0000	
Star rating	0.0266	-0.0259	0.0708	1.0000

Appendix F. Residualized HCC

A potential concern is that the HCC index may capture broader macroeconomic or labor-market conditions (i.e., recessions, changes in unemployment, or shifts in financial-market uncertainty) that independently affect fund flows. To ensure that the effects we document are not driven by such aggregate comovement, we construct a residualized version of the HCC index that purges all variation explained by key macroeconomic controls and broader ESG concern. Specifically, we estimate:

$$\widetilde{HCC}_t = HCC_t - \hat{\beta}' X_t \,,$$

where X_t includes the unemployment rate, the VIX index (market volatility), the Consumer Price Index (CPI), the Economic Policy Uncertainty (EPU) index, and the Media Climate Change Concern (MCCC) index. These variables capture core dimensions of macroeconomic and policy conditions that could jointly affect both media attention and fund flows.

We then re-estimate all baseline regressions using $\widetilde{HCC}_t$ in place of the raw HCC_t index. The results remain highly similar in significance and interpretation (Table F.16). This robustness test confirms that the relationship between attention to human capital concern in the media and mutual fund flows is not mechanically driven by macroeconomic fluctuations. Instead, the residualized HCC index isolates the component of media attention orthogonal to the macro environment, strengthening the interpretation of HCC shocks as an independent driver of investor attention.

Table F.16: Flow-performance sensitivity along residualized HCC
This table reports the estimated effects of the human capital concern (HCC) index on mutual fund flows sensitivity to social performance. Column (1) provides the baseline results. Column (2) uses the residualized HCC index, which removes variation explained by macroeconomic controls (unemployment rate, VIX, CPI, and EPU) and broader ESG concern (MCCC). Standard errors are clustered at the fund level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Dependent variable: Net Flow (%)	
	HCC	Residualized HCC
	(1)	(2)
Return_{t-1}	0.361***	0.362***
	(0.015)	(0.027)
Star_{t-1}	0.709***	0.694***
	(0.014)	(0.025)
Log(Age)_{t-1}	-0.307***	-0.305***
	(0.014)	(0.035)
Log(Size)_{t-1}	-0.418***	-0.415***
	(0.016)	(0.032)
Flow_{t-1} (%)	1.321***	1.322***
	(0.017)	(0.098)
Env_{t-1}	-0.089***	-0.085***
	(0.019)	(0.028)
Soc_{t-1}	0.078***	0.074***
	(0.019)	(0.028)
$\text{HCC}_{t-1} \times \text{Soc}_{t-1}$	0.047***	0.254*
	(0.018)	(0.137)
$\text{HCC}_{t-1} \times \text{Return}_{t-1}$	0.019	0.372***
	(0.015)	(0.115)
$\text{HCC}_{t-1} \times \text{Star}_{t-1}$	0.129***	0.369***
	(0.013)	(0.090)
$\text{HCC}_{t-1} \times \text{Env}_{t-1}$	0.002	0.015
	(0.018)	(0.137)
Observations	263,519	263,519
Style × Time FE	Yes	Yes
COVID	Yes	Yes
R^2	0.058	0.057
Adjusted R^2	0.054	0.054

Appendix G. Placebo test

We further conduct a placebo test following standard permutation procedures to ensure that the documented sensitivity of fund flows to social score in times of heightened HCC is not driven by spurious time variation or random alignment between concern levels and fund characteristics. Specifically, we randomly permute the HCC index across all fund-month observations 1,000 times and re-estimate Equation (5) using these shuffled series. This approach preserves the cross-sectional and distributional properties of HCC while breaking any true temporal association with fund flows.

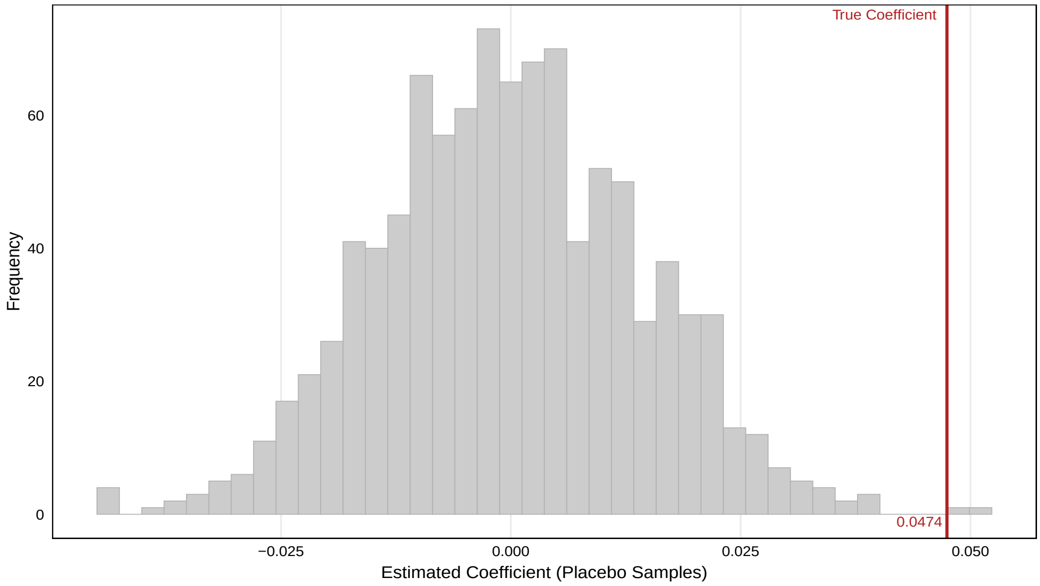
Across the 1,000 estimations, the distribution of the placebo coefficients for the interaction term $HCC \times Soc$ is tightly centered around zero (mean = -0.0001), with none approaching the magnitude of the true estimate (0.047). The resulting empirical p-value is effectively zero, indicating that the observed relationship lies in the extreme tail of the placebo distribution. Panel A of Figure G.4 displays the distribution of placebo coefficients, where the true estimate lies far in the right tail. This result confirms that the observed sensitivity of fund flows to social performance in high-HCC periods reflects a genuine response to value-relevant human capital information rather than random variation in the timing of concern-related news or sampling noise.

To further ensure that the observed sensitivity of fund flows to $HCC \times Soc$ is not driven by fund-level heterogeneity, we perform a placebo test that randomly shuffles the HCC index within each fund rather than across the full panel. This preserves each fund's cross-sectional distribution of HCC exposure while destroying the true temporal alignment. Across 1,000 iterations, the mean placebo coefficient of the interaction term is effectively zero (–0.0035), and none of the placebo coefficients exceed the magnitude of the actual estimate (0.047), yielding an empirical p-value of zero. Panel B of Figure G.4 displays the results. These results mirror those from the global shuffle and confirm that the observed relationship is unlikely to arise from spurious correlation or chance alignment.

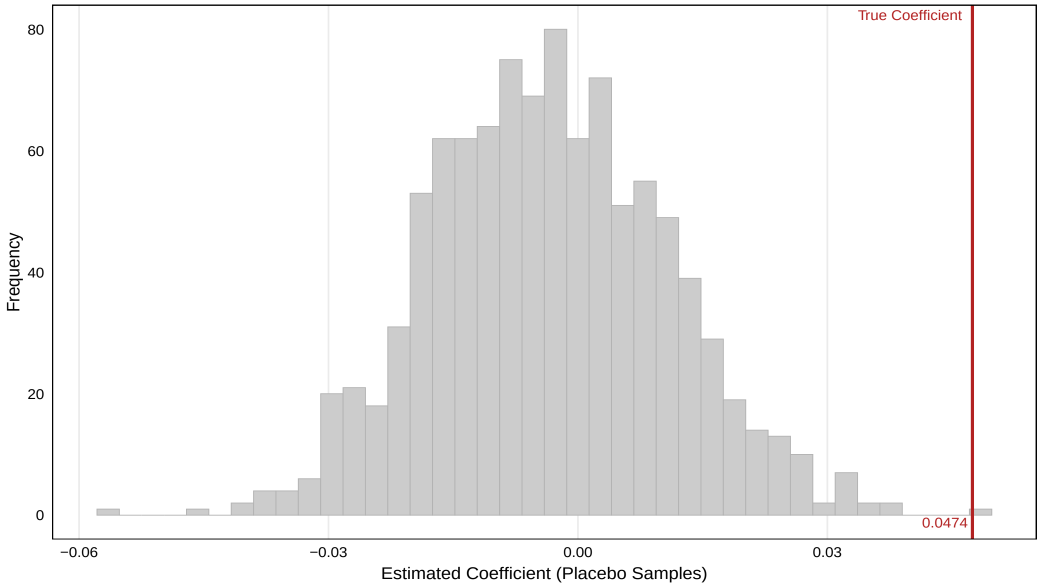
Figure G.4: Placebo distribution of $HCC \times Soc$ coefficients

This figure displays the distribution of 1,000 placebo coefficients of $HCC \times Soc$. Panel A is obtained by randomly permuting the HCC index across all fund-month observations. Panel B is obtained by randomly permuting the HCC values within each fund observation. The red vertical line indicates the true coefficient from the baseline regression.

Panel A: Random Date Permutation Overall



Panel B: Random Date Permutation by Fund



Appendix H. Duration of HCC

Table H.17: Shock duration

This table reports regression results analyzing the impact of social and ESG dimensions on mutual fund flows, and the divergence in reaction between long versus short shocks. A *Short Shock* is a month during which the value of the HCC index reaches the defined range and returns below the range in the following month. Long shocks (*Long Shock*) are months when the HCC index value reaches the defined range and remains within it for more than one period. The intensity ranges of the shock correspond to Low, Moderate, Severe. All variables are standardized. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Net Flow (%)		
	Low (1)	Moderate (2)	Severe (3)
Return_{t-1}	0.376***	0.377***	0.376***
	(0.014)	(0.014)	(0.014)
Star_{t-1}	0.697***	0.697***	0.697***
	(0.014)	(0.014)	(0.014)
Log(Age)_{t-1}	-0.299***	-0.299***	-0.298***
	(0.022)	(0.022)	(0.022)
Log(Size)_{t-1}	-0.426***	-0.426***	-0.426***
	(0.015)	(0.015)	(0.015)
Flow_{t-1} (%)	1.352***	1.352***	1.352***
	(0.016)	(0.016)	(0.016)
ESG_{t-1}	0.014	-0.000	-0.011
	(0.018)	(0.019)	(0.017)
Long Shock × ESG_{t-1}	-0.039***	0.009	0.134***
	(0.034)	(0.032)	(0.043)
Short Shock × ESG_{t-1}	-0.201	-0.046	-0.068
	(0.155)	(0.142)	(0.087)
Observations	274,196	274,196	274,196
Style × Time FE	Yes	Yes	Yes
R^2	0.058	0.058	0.058
Adjusted R^2	0.055	0.055	0.055

Appendix I. Index funds and ETFs flow sensitivity to social performance

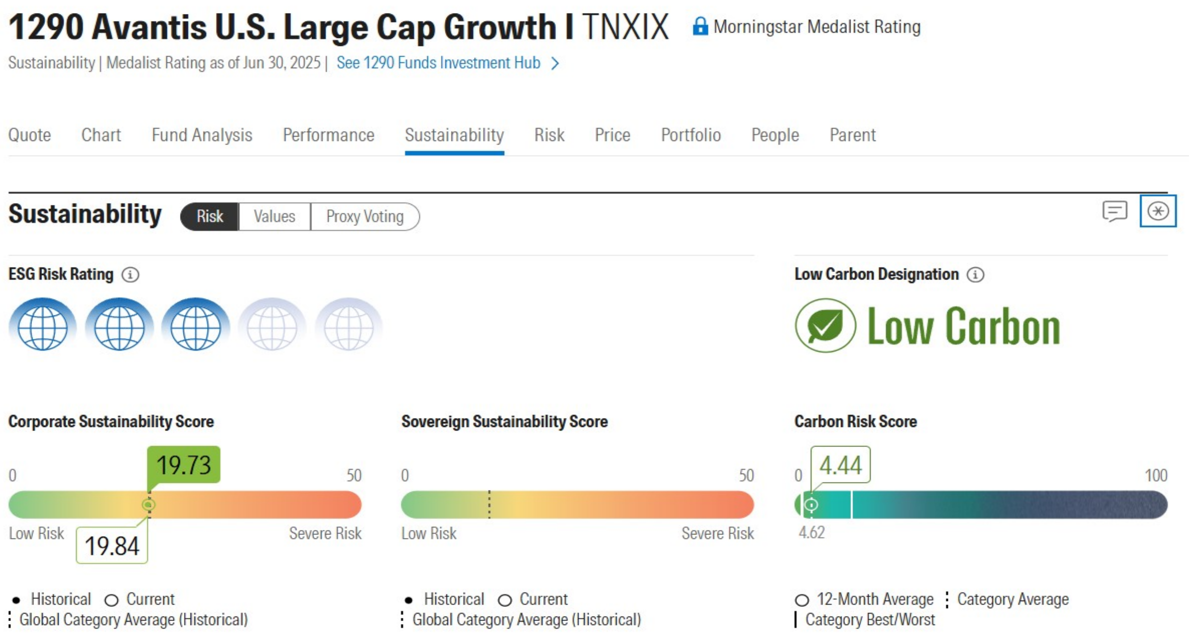
Table I.18: Flow sensitivity to social performance in times of HCC
This table reports regression results analyzing the flow sensitivity to social performance along the level of HCC. Columns 1 and 2 correspond to the index funds and ETFs sample, respectively. All variables are standardized. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Net Flow (%)	
	Index Funds	**ETFs**
	(1)	(2)
Return_{t-1}	1.012***	1.069***
	(0.029)	(0.032)
Star_{t-1}	0.493***	0.588***
	(0.029)	(0.033)
Log(Age)_{t-1}	-0.839***	-0.802***
	(0.053)	(0.074)
Log(Size)_{t-1}	-0.413***	-0.442***
	(0.034)	(0.048)
Flow_{t-1} (%)	0.937***	1.171***
	(0.026)	(0.031)
Soc_{t-1}	0.068*	-0.054
	(0.040)	(0.046)
Env_{t-1}	-0.136***	-0.176***
	(0.039)	(0.045)
$\text{HCC}_{t-1} \times \text{Return}_{t-1}$	0.045	0.081**
	(0.029)	(0.032)
$\text{HCC}_{t-1} \times \text{Star}_{t-1}$	-0.066**	-0.072**
	(0.028)	(0.031)
$\text{HCC}_{t-1} \times \text{Env}_{t-1}$	0.035	0.035
	(0.036)	(0.042)
$\text{HCC}_{t-1} \times \text{Soc}_{t-1}$	0.049	0.046
	(0.038)	(0.044)
Observations	98,169	68,966
Style × Time FE	Yes	Yes
COVID-19	Yes	Yes
R^2	0.072	0.096
Adjusted R^2	0.064	0.084

Appendix J. ESG score

Our primary focus is on the social dimension of ESG. However, the availability and visibility of social risk scores are limited, potentially reducing their prominence in investor decision-making. In particular, the breakdown of the ESG pillar risk score is not directly accessible on Morningstar's public platform; only investors with a Morningstar Direct license can obtain this information.

Figure J.5: The screenshot provides an example of the sustainability information publicly available on Morningstar's website for fund "1290 Avantis U.S. Large Cap Growth I" (ticker: TNXIX). See `https://www.morningstar.com/funds/xnas/tnxix/sustainability`



In contrast, the overall ESG risk score is more widely accessible and frequently used. To assess the robustness of our findings, we repeat prior analyses by replacing the social risk score with the ESG risk score. The results remain consistent with our baseline findings, although the observed effects are somewhat reduced. This is likely due to the broader scope of the ESG score, which incorporates environmental and governance components alongside the social dimension. Table J.19 presents the baseline and intensity results. Figure J.6 displays the estimated smooth effects of ESG score on fund net flows across four groups defined by varying levels of HCC intensity.

Table J.19: Flow-ESG performance sensitivity along social concern

This table reports the results of regression analyzing the flow-sustainable performance sensitivity in times of social concern. The sustainability measure is the ESG score provided by Morningstar direct. All variables are standardized by subtracting their time-series mean and dividing them by their time-series standard deviation. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

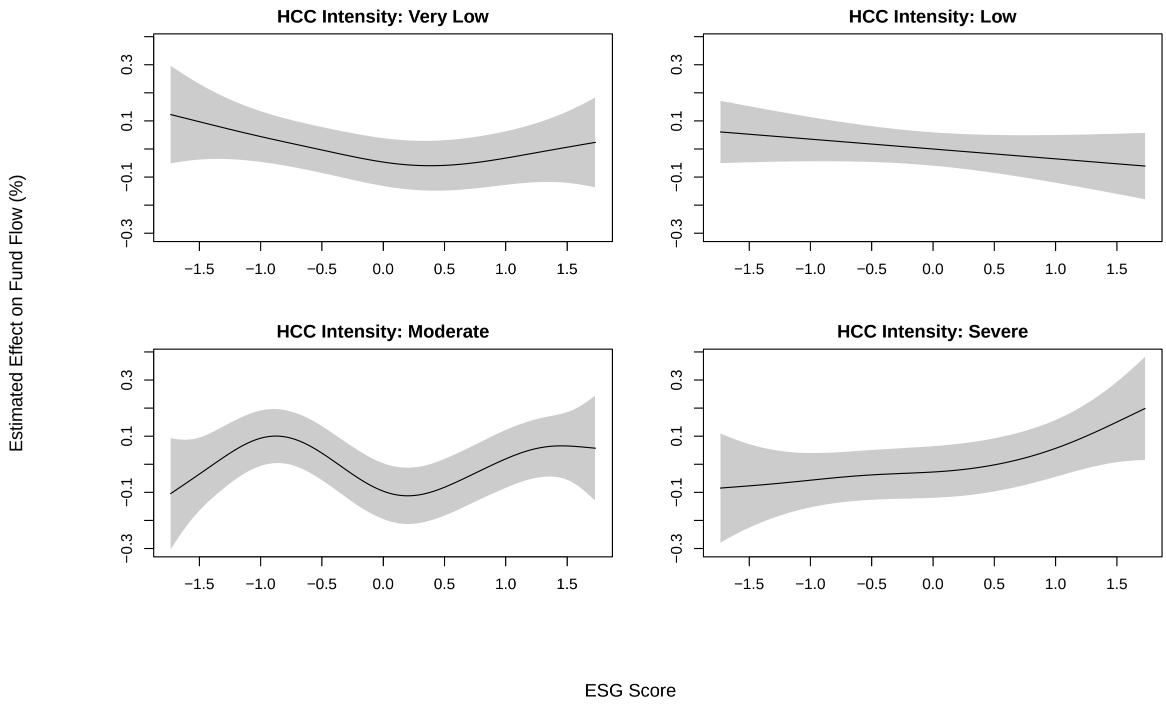
Panel A: Baseline regressions with ESG score

	Dependent variable: Net Flow (%)			
	(1)	(2)	(3)	(4)
Return_{t-1}	0.380***	0.381***	0.378***	0.378***
	(0.012)	(0.012)	(0.014)	(0.014)
Star_{t-1}	0.705***	0.705***	0.701***	0.712***
	(0.013)	(0.013)	(0.013)	(0.014)
Log(Age)_{t-1}	-0.293***	-0.297***	-0.300***	-0.300***
	(0.022)	(0.021)	(0.022)	(0.022)
Log(Size)_{t-1}	-0.427***	-0.422***	-0.427***	-0.427***
	(0.015)	(0.015)	(0.015)	(0.015)
Flow_{t-1} (%)	1.360***	1.365***	1.351***	1.351***
	(0.016)	(0.016)	(0.016)	(0.016)
ESG_{t-1}	-0.013	0.029**	-0.002	0.005
	(0.014)	(0.012)	(0.015)	(0.015)
$\text{HCC}_{t-1} \times \text{ESG}_{t-1}$	0.040***	0.036***	0.035**	0.040***
	(0.012)	(0.012)	(0.015)	(0.015)
$\text{HCC}_{t-1} \times \text{Return}_{t-1}$	0.027**	0.031**	0.013	0.011
	(0.012)	(0.012)	(0.014)	(0.015)
$\text{HCC}_{t-1} \times \text{Star}_{t-1}$	0.106***	0.111***	0.109***	0.118***
	(0.012)	(0.012)	(0.013)	(0.013)
Observations	274,196	274,196	274,196	274,196
Style FE	Yes	No	No	No
Time FE	No	Yes	No	No
Style × Time FE	No	No	Yes	Yes
COVID	No	No	No	Yes
R^2	0.048	0.054	0.059	0.059
Adjusted R^2	0.048	0.053	0.056	0.056
Residual Std. Error	6.069	6.053	6.046	6.046
F Statistic	774.515***	145.679***	18.953***	18.903***

Panel B: Shock intensity and ESG score

	Dependent variable: Net Flow (%)			
	(1)	(2)	(3)	(4)
ESG_{t-1}	0.003	-0.039**	-0.033*	-0.004
	(0.016)	(0.018)	(0.018)	(0.020)
Moderate $\text{HCC}_{t-1} \times \text{ESG}_{t-1}$	0.036	0.040	0.040	-0.025
	(0.028)	(0.028)	(0.028)	(0.035)
Severe $\text{HCC}_{t-1} \times \text{ESG}_{t-1}$	0.090***	0.102***	0.102***	0.074*
	(0.033)	(0.033)	(0.033)	(040)
Observations	274,196	274,196	274,196	274,196
Controls	Yes	Yes	Yes	Yes
COVID	Yes	Yes	Yes	Yes
Style FE	No	Yes	No	No
Time FE	No	No	Yes	No
Style × Time FE	No	No	No	Yes
R^2	0.048	0.048	0.054	0.058
Adjusted R^2	0.048	0.048	0.052	0.055
Residual Std. Error	6.070	6.069	6.053	6.047
F Statistic	990.632***	633.972***	133.021***	18.819***

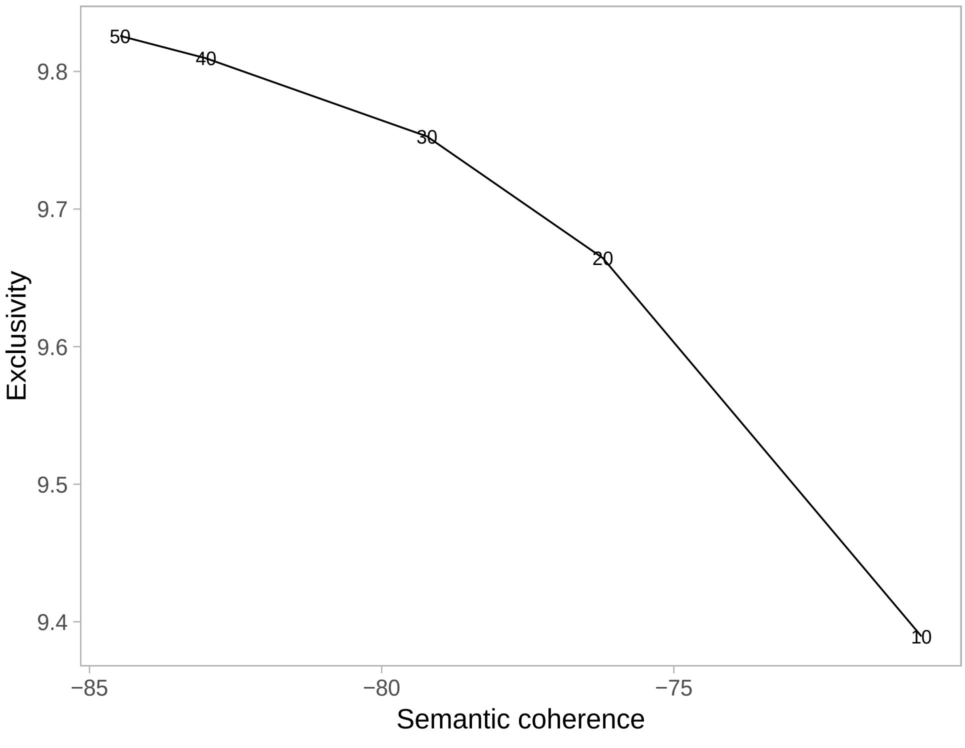
Figure J.6: Generalized Additive Model regression - HCC intensity
The figure displays the estimated smooth effects of ESG score on fund net flows across four groups defined by varying levels of Human Capital Concern intensity, with 95% confidence intervals.



Appendix K. Topics analysis and media sources

To get a better overview of the topics discussed in our set of "work and staff" news, we estimate the Structural Topic Model (STM) of Roberts et al. (2019) on our corpus. This advanced text analysis method extends beyond the traditional Latent Dirichlet Allocation (LDA) model of Blei et al. (2003) by incorporating document-level metadata in the topic estimation process. The STM framework enables the identification of latent topics while accounting for document-specific characteristics, thereby providing a more nuanced understanding of thematic structures. We use newspaper source as one document-specific covariate. This allows us to control for potential source-specific variations in topic distribution. Our topic modeling procedure follows a three-stage approach. First, we calibrate the STM across multiple specifications to determine the optimal number of topics (K) where K ranges from 10 to 50. The optimal number of topics is determined using semantic coherence and exclusivity metrics. Figure K.7 shows the trade-off between semantic coherence and exclusivity across different topic numbers.

Figure K.7: Optimal number of topics - semantic coherence vs. exclusivity
This figure displays the values of semantic coherence (horizontal axis) and exclusivity (vertical axis) for various numbers of topics ($K \in \{10, 20, 30, 40, 50\}$).



We use the "elbow" method to determine the optimal number of topics, which is the point where the improvement in the evaluation metrics starts to slow down significantly. We select 30 topics for the STM estimation as it provides the optimal balance between these two metrics. Second, we assign labels to the identified topics based on two criteria: (i) an analysis of each topic's ten highest-probability words, and (ii) an examination of the articles exhibiting the highest topic prevalence. Finally, to enhance interpretability, we aggregate the individual topics into broader thematic clusters related to human capital issues. We use the Walktrap algorithm to determine the clusters (Pons and Latapy, 2006). Walktrap is an algorithm for detecting communities in networks based on the idea that nodes within the same community are more likely to be visited together during random walks. Using this method, we identify five distinct themes (i.e., clusters of topics) related to human capital issues: (i) "Business Related," (ii) "Labor Advocacy," (iii) "Controversies," (iv) "Regulation," and (v) "Workforce Management". Figure K.8 displays the correlation network of the 30 human capital topics.

Figure K.8: Correlation network of human capital topics

This figure displays the Spearman correlation network for the 30 human capital topics obtained with the structural topic model. To keep the network readable, we display only correlations above 0.35. Each topic is assigned to a thematic cluster that have been determined using the Walktrap algorithm ("Labor Advocacy", "Workforce Management", "Business-Related", "Controversies", "Regulation").

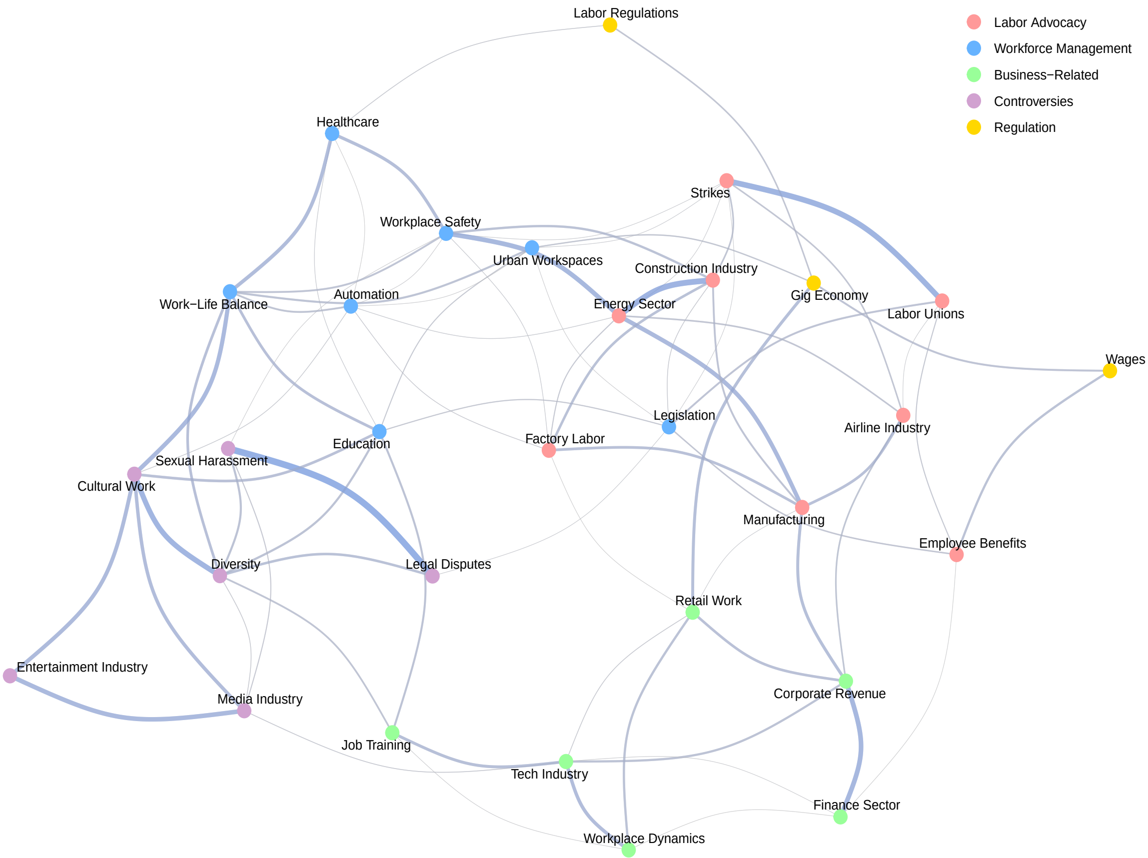


Table K.20 reports the labeled topics together with their ten highest-probability keywords. In Table K.21, we present the unconditional prevalence of topics and themes, along with their average concern scores. The unconditional prevalence of a topic is calculated as the average prevalence of the topic across all news articles. The unconditional prevalence of a theme is the sum of the unconditional prevalences of its constituent topics. The average concern score is a weighted sum of the concern scores of the individual articles, where the weights correspond to the unconditional prevalences. "Business Related" and "Labor Advocacy" are the most prevalent themes in our corpus with prevalence of 26% and 24%, respectively. Both "Controversies" and "Workforce Management" have prevalences just under 20%. The "Regulation" theme has the lowest prevalence.

Table K.20: List of topics together with top ten keywords

This table lists the 30 topics identified in our corpus together with the 10 keywords with the highest probability for each topic. Topics are regrouped into five clusters.

	Business Related
Topic	Top ten keywords in terms of probability
Corporate Revenue	company, year, business, sale, market, revenue, cost, plan, share, profit
Workplace Dynamics	company, employee, worker, manager, office, time, work, people, executive, day
Tech Industry	technology, data, company, system, software, service, information, tech, product, people
Retail Work	store, customer, retailer, chain, warehouse, retail, sale, company, year, worker
Finance Sector	firm, bank, investment, fund, investor, money, client, loan, asset, bonus
Job Training	job, program, year, skill, career, employer, work, training, people, firm

	Labor Advocacy
Topic	Top ten keywords in terms of probability
Strikes	strike, protest, day, train, worker, bus, rail, protester, port, railroad
Employee Benefits	benefit, plan, tax, pension, cost, year, health, employer, insurance, worker
Factory Labor	worker, factory, company, labor, supplier, condition, group, fire, retailer, safety
Energy Sector	oil, gas, energy, plant, water, worker, industry, power, fuel, reactor
Airline Industry	airline, pilot, flight, carrier, plane, airport, travel, aircraft, jet, passenger
Manufacturing	plant, production, company, factory, car, vehicle, manufacturing, part, job, auto maker
Labor Unions	union, worker, contract, agreement, member, labor, strike, deal, year, wage
Construction Industry	government, country, project, contractor, official, construction, world, contract, region, security

	Controversies
Topic	Top ten keywords in terms of probability
Sexual Harassment	investigation, complaint, board, allegation, report, statement, agency, letter, charge, sexual harassment
Diversity	woman, man, diversity, discrimination, percent, minority, gender, race, group, policy
Media Industry	news, network, media, show, video, people, editor, post, advertising, staff
Legal Disputes	case, court, lawsuit, lawyer, law, decision, claim, suit, judge, settlement
Cultural Work	people, life, world, thing, way, book, story, work, time, word
Entertainment Industry	player, team, game, season, owner, year, actor, studio, sport, film

	Regulation
Topic	Top ten keywords in terms of probability
Labor Regulations	worker, rule, employer, agency, administration, mandate, health, coronavirus, requirement, regulation
Wages	worker, job, wage, year, economy, hour, percent, rate, minimum wage, increase
Gig Economy	restaurant, driver, worker, drivers, hour, food, company, service, business, ride

	Workforce Management
Topic	Top ten keywords in terms of probability
Education	school, student, teacher, education, university, college, year, class, campus, district
Healthcare	hospital, drug, doctor, health, care, patient, nurse, cancer, study, treatment
Workplace Safety	safety, accident, explosion, mine, miner, death, fire, report, worker, injury
Legislation	state, bill, law, campaign, administration, group, legislation, proposal, issue, lawmaker
Urban Workspaces	city, building, office, hotel, area, mayor, home, year, resident, housing
Automation	day, year, time, machine, robot, food, training, hour, room, foot
Work-Life Balance	family, child, police, year, day, man, home, officer, mother, people

Table K.21: Topics' prevalence and concern score

This table reports the 30 topics' unconditional prevalence and average concern score. We compute the unconditional prevalence of a topic as the average of the topic prevalences across all news articles. For a theme, the unconditional prevalence is the sum of its topics' unconditional prevalences. The average concern score is computed as a weighted sum of the articles' score, where the weights correspond to the topic (or the theme) unconditional prevalences.

	Overall		NYT		WSJ	
	Unconditional Prevalence	Average Concern Score	NYT Prevalence	Average Concern Score	WSJ Prevalence	Average Concern Score
Business Related	26.42	0.26	15.71	0.29	32.71	0.25
Corporate Revenue	6.96	0.26	2.94	0.28	9.33	0.26
Workplace Dynamics	6.26	0.27	5.02	0.30	6.99	0.26
Tech Industry	3.49	0.26	1.93	0.30	4.41	0.25
Retail Work	2.56	0.24	1.47	0.31	3.21	0.22
Finance Sector	3.64	0.30	1.78	0.30	4.73	0.30
Job Training	3.50	0.19	2.57	0.22	4.04	0.18
Labor Advocacy	23.82	0.35	21.50	0.37	25.19	0.34
Strikes	2.74	0.38	3.53	0.38	2.27	0.39
Employee Benefits	3.71	0.29	2.71	0.29	4.30	0.29
Factory Labor	1.69	0.45	2.04	0.50	1.49	0.41
Energy Sector	2.05	0.60	1.75	0.73	2.22	0.54
Airline Industry	2.10	0.42	1.15	0.41	2.66	0.42
Manufacturing	3.76	0.29	2.04	0.33	4.77	0.28
Labor Unions	5.79	0.26	6.64	0.26	5.29	0.25
Construction Industry	1.99	0.43	1.64	0.46	2.19	0.42
Controversies	19.96	0.32	27.65	0.32	15.43	0.32
Sexual Harassment	4.30	0.41	5.05	0.43	3.86	0.40
Diversity	2.93	0.27	4.76	0.28	1.85	0.25
Media Industry	2.87	0.26	3.81	0.26	2.32	0.25
Legal Disputes	3.66	0.39	4.17	0.40	3.36	0.38
Cultural Work	3.48	0.28	5.70	0.29	2.18	0.27
Entertainment Industry	2.71	0.24	4.17	0.23	1.86	0.24
Regulation	10.60	0.30	11.36	0.33	10.16	0.29
Labor Regulations	2.75	0.44	2.80	0.51	2.72	0.40
Wages	5.55	0.25	5.81	0.26	5.40	0.24
Gig Economy	2.30	0.28	2.75	0.30	2.03	0.26
Workforce Management	19.20	0.41	23.77	0.45	16.51	0.38
Education	2.15	0.28	2.89	0.28	1.71	0.28
Healthcare	1.86	0.43	2.16	0.48	1.69	0.40
Workplace Safety	2.81	0.89	3.60	0.94	2.35	0.85
Legislation	4.76	0.31	6.00	0.32	4.03	0.31
Urban Workspaces	2.76	0.27	2.65	0.34	2.83	0.23
Automation	2.01	0.30	2.08	0.38	1.96	0.26
Work-Life Balance	2.85	0.39	4.39	0.41	1.94	0.37

Since our HCC index is composed of two sources with divergent focus,[17] we investigate whether the source of news influences our results. To make sure that our results are not biased by the newspapers selected to construct our HCC index, we rerun our baseline regression with source-specific indices. Table K.22 reports the results. The findings suggest that the sensitivity of mutual fund flows to social performance increases during periods of increased social concern, but this relationship is only valid when the HCC index is derived from the NYT. One explanation for this divergence in significance might be content-related, as the main reaction occurs in response to workforce management issues.

[17] The New York Times is a left-leaning newspaper, while the Wall Street Journal is right-leaning.

Table K.22: Newspaper sources - The Wall Street Journal vs. the New York Times
This table reports the results of regression analyzing the flow-performance sensitivity in times of social concern, given different sources of newspapers. Columns 1 and 2 report the results using the NYT source-specific index. Columns 3 and 4 report the results using the WSJ source-specific index. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Net flow (%)			
	NYT	NYT	WSJ	WSJ
	(1)	(2)	(3)	(4)
$\text{HCC}_{t-1} \times \text{Return}_{t-1}$	0.033**		-0.001	
	(0.014)		(0.015)	
$\text{HCC}_{t-1} \times \text{Star}_{t-1}$	0.117***		0.089***	
	(0.013)		(0.013)	
$\text{HCC}_{t-1} \times \text{Env}_{t-1}$	0.017		-0.015	
	(0.019)		(0.018)	
$\text{HCC}_{t-1} \times \text{Soc}_{t-1}$	0.049***		0.024	
	(0.019)		(0.017)	
Index Business $\text{Related}_{t-1} \times \text{Return}_{t-1}$		0.041*		0.049**
		(0.021)		(0.023)
Index Business $\text{Related}_{t-1} \times \text{Star}_{t-1}$		0.053***		-0.015
		(0.019)		(0.020)
Index Business $\text{Related}_{t-1} \times \text{Env}_{t-1}$		0.044*		0.017
		(0.026)		(0.027)
Index Business $\text{Related}_{t-1} \times \text{Soc}_{t-1}$		0.023		-0.007
		(0.026)		(0.027)
Index Labor $\text{Advocacy}_{t-1} \times \text{Return}_{t-1}$		0.039*		-0.112***
		(0.022)		(0.022)
Index Labor $\text{Advocacy}_{t-1} \times \text{Star}_{t-1}$		-0.032		-0.041**
		(0.019)		(0.019)
Index Labor $\text{Advocacy}_{t-1} \times \text{Env}_{t-1}$		-0.042		0.014
		(0.026)		(0.028)
Index Labor $\text{Advocacy}_{t-1} \times \text{Soc}_{t-1}$		-0.044*		-0.069**
		(0.026)		(0.028)
Index $\text{Controversies}_{t-1} \times \text{Return}_{t-1}$		0.010		-0.008
		(0.022)		(0.019)
Index $\text{Controversies}_{t-1} \times \text{Star}_{t-1}$		0.019		0.011
		(0.020)		(0.016)
Index $\text{Controversies}_{t-1} \times \text{Env}_{t-1}$		-0.022		-0.029
		(0.034)		(0.023)
Index $\text{Controversies}_{t-1} \times \text{Soc}_{t-1}$		-0.036		0.003
		(0.033)		(0.023)
Index $\text{Regulation}_{t-1} \times \text{Return}_{t-1}$		0.075***		0.086***
		(0.019)		(0.018)
Index $\text{Regulation}_{t-1} \times \text{Star}_{t-1}$		-0.035**		-0.026*
		(0.017)		(0.015)
Index $\text{Regulation}_{t-1} \times \text{Env}_{t-1}$		-0.009		-0.030
		(0.022)		(0.019)
Index $\text{Regulation}_{t-1} \times \text{Soc}_{t-1}$		0.004		-0.009
		(0.021)		(0.019)
Index Workforce $\text{Management}_{t-1} \times \text{Return}_{t-1}$		-0.078***		0.024
		(0.026)		(0.022)
Index Workforce $\text{Management}_{t-1} \times \text{Star}_{t-1}$		0.115***		0.154***
		(0.022)		(0.020)
Index Workforce $\text{Management}_{t-1} \times \text{Env}_{t-1}$		0.035		-0.014
		(0.036)		(0.029)
Index Workforce $\text{Management}_{t-1} \times \text{Soc}_{t-1}$		0.120***		0.108***
		(0.035)		(0.029)
Observations	263,519	263,519	263,519	263,519
Controls	Yes	Yes	Yes	Yes
COVID	Yes	Yes	Yes	Yes
Style × Time FE	Yes	Yes	Yes	Yes
R^2	0.058	0.058	0.057	0.058
Adjusted R^2	0.054	0.055	0.054	0.055
Residual Std. Error	5.994	5.993	5.994	5.993
F Statistic	17.744***	17.530***	17.669***	17.524***

We therefore rerun the themes' horse race analysis using our source-specific indices. Consistent with the results obtained using the aggregated *HCC* index, we find that workforce management is the main topic influencing the investor decision-making process for both sources. We therefore relate the non-significance of the WSJ as a corpus of news to the lower predominance of workforce management news. Workforce management concern, including safety conditions and work-life balance initiatives, prove crucial as they directly influence employee satisfaction and, consequently, organizational success.

This difference in the baseline regression arises from the divergence in the prevalence of topics (and themes) covered by the newspapers. Table K.23 highlights systematic differences in topic prevalence between the NYT and the WSJ, as estimated by a beta regression model. The Wall Street Journal demonstrates a pronounced focus on business and industry-oriented topics, whereas the New York Times allocates greater attention to sociocultural issues and workplace controversies, including diversity initiatives, sexual harassment cases, and workplace culture dynamics. This divergence in theme prevalence suggests a difference in the type of concern conveyed by the news, and therefore a divergence in investor reaction regarding their investment behavior. The newspaper source itself does not directly influence the results; rather, it is the predominance of content relating to concern on workforce management that drives the significance of the findings when the indices are aggregated.

Table K.23: Differences in Topic Prevalence Across News Sources
This table reports the results of the beta regression for topic prevalence. Specifically, the intercept represents the baseline topic prevalence for the New York Times. The source coefficient indicates the effect of the Wall Street Journal on topic prevalence, capturing the deviation in topic prevalence from the New York Times baseline. The beta regression model is specified as: $\text{logit}(\mu_i) = \beta_0 + \beta_1 \cdot \text{Source}_{\text{WSJ}} + \epsilon_i$, where μ_i is the expected topic prevalence for document i, and Source_{WSJ} is a binary variable equal to 1 if the document is from the Wall Street Journal and 0 otherwise. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Cluster	Topic	Intercept Estimate	Intercept SE	Source Estimate	Source SE
Business Related	Corporate Revenue	-2.935***	0.016	0.626***	0.016
	Workplace Dynamics	-2.852***	0.013	0.273***	0.014
	Tech Industry	-3.477***	0.016	0.365***	0.016
	Retail Work	-3.747***	0.016	0.324***	0.016
	Finance Sector	-3.442***	0.016	0.413***	0.016
	Job Training	-3.299***	0.015	0.122***	0.016
Controversies	Sexual Harassment	-2.937***	0.015	-0.150***	0.016
	Diversity	-3.171***	0.016	-0.397***	0.016
	Media Industry	-3.295***	0.015	-0.168***	0.015
	Legal Disputes	-3.107***	0.015	-0.143***	0.016
	Cultural Work	-2.948***	0.013	-0.534***	0.015
	Entertainment Industry	-3.227***	0.017	-0.194***	0.016
Labor Advocacy	Strikes	-3.362***	0.016	-0.181***	0.016
	Employee Benefits	-3.202***	0.016	0.143***	0.016
	Factory Labor	-3.774***	0.017	-0.052***	0.016
	Energy Sector	-3.793***	0.017	0.152***	0.016
	Airline Industry	-3.786***	0.018	0.235***	0.016
	Manufacturing	-3.341***	0.017	0.356***	0.016
	Labor Unions	-2.649***	0.016	-0.113***	0.016
	Construction Industry	-3.961***	0.014	0.142***	0.015
Regulation	Labor Regulations	-3.481***	0.015	0.034**	0.015
	Wages	-2.700***	0.016	0.004	0.016
	Gig Economy	-3.559***	0.016	-0.063***	0.016
Workforce Management	Education	-3.558***	0.017	-0.178***	0.016
	Healthcare	-3.797***	0.016	-0.075***	0.016
	Workplace Safety	-3.270***	0.018	-0.087***	0.016
	Legislation	-2.794***	0.014	-0.236***	0.015
	Urban Workspaces	-3.469***	0.015	-0.040***	0.015
	Automation	-3.781***	0.015	-0.010	0.015
	Work-Life Balance	-3.236***	0.014	-0.400***	0.015