

When Social Issues 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

We study how retail investors respond to the social dimension of Environmental, Social and Governance (ESG) criteria when social risk becomes salient. To do so, we construct a novel news-based Human Capital Concern (HCC) index that captures changes in media attention to financially material workforce-related issues and examine its role in shaping mutual fund flows from 2015–2023. We show that retail flows become significantly more sensitive to funds' social risk scores during periods of elevated HCC, with effects concentrated in severe and persistent episodes. In contrast, no comparable response arises when media attention centers on ethical or human-rights topics with lower financial materiality. We further show that high-social-score funds outperform following high-HCC periods, in a pattern consistent with a risk-based repricing of social exposures rather than temporary demand pressure. Our findings suggest that retail investors integrate social performance when it becomes financially relevant but does not rule out the presence of non-pecuniary preferences. Overall, the results highlight the state-dependent financial materiality of the social pillar of ESG.

Keywords: Social, Human Capital, Textual Analysis, Mutual Funds Flows, Retail Investors

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^{*}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

Whether (and why) retail investors integrate Environmental, Social, and Governance criteria into their investment decisions remains subject to debate. The early literature largely interprets 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, rather than trading on non-pecuniary motives alone (Li et al., 2024). Our paper reconciles these seemingly conflicting findings by examining whether retail investors perceive social performance as financially material. In times where public discourse asserts that “investors seek out ‘S’ factor in ESG” (Financial Times, 2022), little is known on whether social considerations really influence actual portfolio choices.¹ Using data on U.S. retail investors, we provide novel evidence of investor sensitivity towards the social risk factors of their investments in times of extreme social concerns, blurring the separation between social value or social values motivation. Understanding whether social factors are priced as sources of financial risk is particularly important given the fiduciary duty of the asset management industry, which may extend to ESG considerations when they are financially material.

Our analysis focuses on retail investors, who represent a substantial share of investment activity in U.S. financial markets through their holdings of mutual funds. According to the Investment Company Institute (ICI), household investors account for approximately 88% of total assets invested in U.S. mutual funds. As a result, mutual fund flows provide a natural setting to infer retail investors’ sensitivity to the social characteristics of their investments. For that, we examine retail and institutional investment flows into 5,014 unique US-domiciled equity mutual funds over the period 2015-2023. The main focus of our study is on the sample of retail mutual funds. We rely on Morningstar’s social risk score, information that investors can access through ESG rating agencies, to assess the social performance of investment funds.

We start by setting up an experiment where we assume limited attention and cognitive biases of retail investors (Kahneman and Tversky, 1979; Shefrin and Statman, 2000; Hirshleifer and Teoh, 2003). Within this theoretical framework, literature has shown that individual

¹See: <https://www.ft.com/content/a5e8b3f0-41a6-443d-a290-f794f7e9df93?>

trading behavior is influenced by media coverage and short-term information signals (Da et al., 2011; Peress, 2014; Docherty and Hurst, 2018), and that investors are more likely to trade attention-grabbing stocks or invest in “hot style” investment funds (Cooper et al., 2005; Barber and Odean, 2008). We run a quasi-natural experiment on investor attention by constructing a novel news-based index that captures the evolution of investor attention to human capital risks through the lens of two major U.S. newspapers: The New York Times (NYT) and the Wall Street Journal (WSJ).² Our empirical setup is closely related to Li et al. (2024), with two key distinctions. We focus explicitly on the social dimension of ESG and study retail investors’ allocation decisions using mutual fund flows rather than individual trading orders. In light of Sloan’s (2024) critique, this setting is particularly well-suited to assess whether retail investors consider social performance to be financially material. While our approach does not rule out non-pecuniary social preferences in normal times, we show that investor sensitivity to social performance increases significantly when social concern becomes salient.

Our Human Capital Concern (hereafter HCC) index tracks the evolution of the concern over human capital issues by combining a sentiment lexicon, which gauges the degree of negativity, with a risk lexicon, which tracks discussions of adverse events. We focus on human capital as it is one of the most economically relevant components of the social pillar within the ESG framework. Human capital is widely recognized as a key driver of firm success in the finance literature (Edmans, 2011; Shan and Tang, 2023; Edmans et al., 2024)), and it constitutes one of the five dimensions considered as material for investors by the Sustainability Accounting Standards Board (SASB).³ To our knowledge, this is the first index to specifically capture concerns related to the social dimension of ESG.⁴

We start by running a pooled-OLS regression on fund flows, where the testing variable is the social performance of the fund that we interact with our HCC index. Our analysis reveals that investors’ interest in social performance of their investments varies with the

²See Statista: Circulation of the Biggest Daily Newspapers in the US

³The 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>

⁴We acknowledge that textual analysis has been widely applied to construct environmental- or ESG-related indices (Engle et al., 2020; Ardia et al., 2023; De Nard et al., 2024; Sautner et al., 2023; Faccini et al., 2023). However, no comparable index exists for the social pillar so far.

level, the intensity, and the duration of human capital concerns communicated in the media. We further examine the non-linearity of the results using a Generalized Additive Model (GAM) and show that investors' sensitivity to social performance becomes economically and statistically significant at extreme levels of concern. We observe that a one standard deviation increase in HCC increases the flow sensitivity to social scores by more than 60%.

The increased sensitivity that we observe following severe HCC provides evidence that investors are not indifferent to the social performance of their investment, but leaves open the question of which specific motives drive investors to reallocate funds. Although we cannot definitively identify the specific motive, our results are consistent with the fact that financial motives play an important role in whether investors hold sustainable investments. Specifically, interest in the social dimension appears to be driven by risk aversion to social factors, which in turn depends on the dominant concern in the economy. Similar findings have been shown regarding the environmental dimension of ESG. Recent research demonstrates that some events conveying unexpected shifts in climate concerns might be responsible for temporary positive returns either by increasing customer demand for green products (Pastor et al., 2022; Ardia et al., 2023) or by encouraging investors to hedge climate risks (Engle et al., 2020; Pastor et al., 2022; Ardia et al., 2023).

While our set up seems particularly well suited to examine whether retail investors show pecuniary preferences for social factors, it does not elude the possibility for investors to have non-pecuniary preferences for social factors in normal times. Indeed, one could alternatively argue that investors incorporate social factors into their decisions not only for financial reasons but also for moral motivations. Drawing on moral development theory (Kohlberg, 1981), individuals form ethical values that might influence capital allocation. This notion is supported by evidence that investors increasingly align portfolios with social values and that social identification shapes risk perceptions (Bonnefon et al., 2025; Bauer and Smeets, 2015). Moral motivations are generally stable, linked to identity and self-image (Brekke et al., 2003; Akerlof and Kranton, 2000; Mayr and Freund, 2020). Consequently, investors' ethical decisions are more shaped by peer socialization than media exposure. These theoretical frameworks suggest that values-driven investors should maintain their capital allocation despite increasing concerns reported in the media. Our results show a change in sensitivity

to social criteria and, therefore, do not support this alternative explanation.

To further support our results on the financial motivation of retail investors to reallocate following periods of elevated HCC, we develop an alternative index focusing on media coverage of ethical issues (e.g., human rights and individual freedom topics). Although Social Capital is also included within the SASB Materiality Map, it is designated as financially material for substantially fewer industries than Human Capital. Using this Human Rights Concern (HRC) index, we find no impact on fund flow sensitivity to social scores. These results further confirm our previous evidence supporting the idea that retailers value the social performance of their investment mainly for financial value rather than ethical values.

A key question is whether investors benefit from reallocating to funds with high social performance. We further investigate whether funds with high social performance outperform those with lower social performance. Following periods of elevated human-capital concerns, our results provide evidence that funds with high social scores experience higher return than the others. This observed outperformance can theoretically operate through several interconnected channels. First, a demand-based channel implies that increased attention or investor awareness of social risks leads to higher fund inflows, mechanically driving up prices and subsequent returns. Second, a risk-based valuation channel posits that increased salience leads investors to reassess expected payoffs and the risk profile of portfolios concentrated in high-S firms. Finally, high-social-score funds may indirectly benefit from the operational advantages of their underlying holdings. These mechanisms indicate that fund outperformance can be driven by both investor allocation behavior and the inherent resilience of socially responsible portfolios. Our empirical evidence allows us to disentangle the proportion of the effect that comes from both channels. We find that flows account for only a small fraction of the effect. Because the same temporary outperformance of high-social-score portfolios is observed in passive index funds and social-tilted ETFs, which do not engage in discretionary stock selection and receive minimal flows, the effect cannot be attributed to fund-level capital movements, manager skill, or screening behavior. Taken together, the hump-shaped return pattern is more consistent with a market-wide repricing of social risk that becomes salient following episodes of elevated social concern and subsequently fades as attention normalizes.

Taken together, our paper contributes to the debate highlighted in Starks' (2023) presi-

dential address at the AFA on whether investors incorporate sustainability criteria into their investment decisions because they perceive them as financially value-relevant or because they align with their personal values by providing novel evidence on retail investors' valuation of social performance. This debate resonates with a growing literature that seeks to disentangle the financial and non-financial motivations behind sustainable investment. Some studies highlight social preferences and signaling as central drivers (Riedl and Smeets, 2017; Bauer et al., 2021), while others document heterogeneity across investor types in their willingness to sacrifice returns for ESG considerations (Gutsche and Ziegler, 2019; Barber et al., 2021). Yet another strand emphasizes financial motivations, showing that investors respond primarily to material risks and returns rather than moral concerns (Døskeland and Pedersen, 2016; Gantchev et al., 2024), consistent with the distinction between value-motivated and values-motivated investors (Pedersen et al., 2021). Our findings help reconcile this literature by showing that retail investors' attention to social factors is state-dependent, rising when social risks are financially salient and fading when ethical concerns lack 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.

Importantly, our paper contributes to the scarce literature on the social dimension of ESG. Although the existing literature has already examined whether ESG ratings matter for investment flows (Ammann et al., 2019; Hartzmark and Sussman, 2019), investor interest in the social performance of their investment has received little attention. Performing firm-level analysis, a body of literature investigates the effect of social criteria, particularly employee satisfaction, on firm performance. Edmans (2011) and Edmans et al. (2024) find that employee satisfaction positively influences firm value and that it is not fully priced by the market. Similarly, Shan and Tang (2023) show that employee satisfaction acts as a strategic asset, enhancing firm resilience and stability in adverse times. Their study finds that firms with high employee satisfaction outperform during crises like COVID-19, showing better stock and operating performance, especially in knowledge-based industries.

More broadly, our paper is also related to the strand of literature that investigates investor interest in sustainability. Recent papers study the consideration of non-financial criteria in

the investment decision-making process (Hartzmark and Sussman, 2019; Ammann et al., 2019; Ceccarelli et al., 2024). Besides, recent research suggests that attention to ESG scores might fade over time (Gantchev et al., 2024). However, these studies do not account for potential time variations in their conclusions. Other research has shown that investors display greater loyalty to ESG performers than to non-ESG performers (Bollen, 2007; Benson and Humphrey, 2008). We show that investor interest in the social performance of their investments is conditional on the level of social risks in the market, as captured by the media attention to social concerns.

The rest of the paper is organized as follows. Section 2 presents the methodology used for the news-based indices capturing human capital concerns. Section 3 describes the data. Section 4 reports empirical results on the time-varying fund flow sensitivity to social performance. Section 5 conducts additional tests to corroborate the interpretation of our results. Finally, Section 6 concludes the paper.

2. Measuring social concerns

We develop a novel index of social concern following Ardia et al. (2023). To our knowledge, this is the first index to specifically capture concerns 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 concerns around the social dimension. This measurement of concern is performed through lexicons from the LIWC-22 software (Pennebaker et al., 2015). The program contains a text analysis application capable of studying the emotional components present in texts; see <https://www.liwc.app>.

Relying on a lexicon-based approach for extracting social concerns 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 $t = 1, \dots, T$, source s publishes $n = 1, \dots, N_{t,s}$ 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 in risk perception). Consistent with Ardia et al. (2023), the concerns are 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 a fixed time range from 2010 to 2015. Second, we divide each source-specific index by its standard deviation across the entire 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 concerns for that day to account for the fact that increased media attention always strengthens concerns, 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 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:

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

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.

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 sustain-

⁵A 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.

⁶See <https://www.morningstar.com/investing-definitions/portfolio-social-risk-score> and <https://www.morningstar.com/investing-definitions/portfolio-environmental-risk-score>.

ability 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 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. Retail funds

⁷We 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.

on average experience more outflows, have a lower Star rating, are 5 years older and slightly larger than institutional funds. On average, both types of funds have similar monthly return.

[Insert Table 2 about here.]

Table 3 describes how the sustainability metrics are distributed over the sample. Panel A provides summary statistics for these characteristics for all funds in our sample from January 2015 to September 2019, that is, prior 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. Empirical results

We first estimate a pooled OLS regression to test the monthly sensitivity of flows to the sustainability performance measures (social and ESG scores). The model stands as follows:

$$\text{Flow}_{i,t} = \alpha_i + \beta_1 \text{Soc}_{i,t-1} + \beta_2 \text{CTRL}_{i,t-1} + \varepsilon_{i,t}, \quad (4)$$

where, $\text{Flow}_{i,t}$ is the dependent variable and represents the percentage net flow of fund i in month t , $\text{Soc}_{i,t-1}$ is the percentile-ranked social score of fund i in month $t - 1$. $\text{CTRL}_{i,t-1}$ accounts for the usual flow drivers at time $t - 1$: the logarithm of the total value of Assets Under Management in the fund i , the logarithm of fund's age (i.e., 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

⁸We 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 remain similar in all specifications.

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 first estimate Equation (4) in a cross-sectional approach. Specifically, for each month t , we run the regression across all funds i to capture the cross-sectional variation in fund flows. This method conditions on the prior-period characteristics of each fund but does not incorporate temporal dependencies between funds over different time periods. The flow-sustainability sensitivity corresponds to the slope β_1 . We group the monthly estimates of flow sensitivity into 4 buckets, based on the quartiles 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 flow-sustainability sensitivity, along with 95% confidence intervals, by quartile of social concerns. Panel A reveals a nonlinear, upward-sloping relationship between flow-sensitivity and social performance across quartiles of HCC. Flow-sensitivity to social scores exhibits modest positive values during periods of low concern (0.10 in the first quartile) and increases marginally in the second quartile (0.18), but the flow-sensitivity to social score rises strongly in the third (0.41) and fourth (0.67) quartiles. This convex shape suggests that the impact of social performance on fund flows is minimal when human capital issues are not salient to investors, but becomes increasingly important as concerns about human capital increase. Using the overall ESG score as a robustness test, Panel B corroborates this pattern. While flow-sensitivity remains negative across the bottom three HCC quartiles, it becomes positive in the top quartile, supporting the conclusion that the ESG performance-flow relationship strengthens during periods of heightened HCC. Collectively, both panels suggest that investor responsiveness to non-financial performance metrics is contingent upon the level of human capital concerns.

[Insert Figure 2 about here.]

4.1. Baseline analysis

Building on this result, we modify the previous regression model to more formally test whether flow sensitivity to social performance is conditional on social concerns. Specifically,

we introduce interaction terms between social performance and the HCC index in Equation 4. The modified model stands 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 $t - 1$. The interaction term (e.g., $\text{Soc}_{i,t-1} \times \text{HCC}_{t-1}$) captures how the sensitivity of fund flows to Soc) depends on the level of global concern about social issues. 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, and ensure that the effect captured by the interaction term corresponds to a change in investor interest in social performance. Table 4 presents the estimation results of Equation (5).

[Insert Table 4 about here.]

Across all specifications, we find a positive and statistically significant coefficient on $\text{Soc} \times \text{HCC}$, indicating that heightened levels of social concerns (proxied by the HCC variable) amplify the sensitivity of mutual fund flows to the social score. These results have to be compared with regard to the situation when the social concern level is average: in this case, mutual funds with higher social performance receive larger flows than funds with lower social performance. The results are robust to the inclusion of style fixed-effects (Column 1), time fixed-effects (Column 2), and become even stronger with the inclusion of style-by-time fixed-effects (Column 3). In the latter setting, a one-standard-deviation increase in Soc is associated with a 0.063 percentage point increase in net flows. The coefficient of the interaction term indicates that for each additional one-standard-deviation increase in HCC , the sensitivity of flows to social performance rises by 0.047 percentage points. The consideration of social performance in investment decision strengthens by more than 60% following a one standard deviation increase in HCC level. This latter specification compares funds within the same style category at each point in time, effectively isolating the variation in flows from style-related influences. Consequently, it reduces concerns that the observed

relationship between flows and the social score is driven by style effects correlated with Soc , thereby reinforcing the validity of our findings.

The COVID-19 crisis coincides with a pronounced peak in the HCC index from January 2020 to July 2020. This suggests a significant shift in public sentiment towards social issues such as health, inequality, and working conditions. Isolating this period is therefore essential to ensure that our overall results are not driven by these crisis-specific dynamics.⁹ We add a dummy variable and its interaction with Soc_{t-1} to capture the effect. Column (4) presents the results.¹⁰ Controlling for the specific impact of the COVID-19 crisis, fund flows become even more sensitive to social scores in times of elevated concern.

In Column 5, we add interaction terms of HCC with other performance metrics (*Return*, *Star*, *Env*) as they can be correlated with the fund’s social performance. The cross effects 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 a 0.361 percentage point increase in net flows in the following month. Besides, a standard-deviation increase in the star rating is associated with a 0.709 percentage point increase in flows. These results suggest that, when *HCC* is average, funds with better financial performance attract significantly higher flows. Crossing these effects with our HCC index, we observe that, when the HCC level increases by one standard deviation, this relationship strengthens by 5% and 18% for short-term and long-term financial performance, respectively. This suggests that higher attention to human capital issues (such as labor practices, employee well-being, and diversity) correlates with enhanced focus on financial performance.

We interpret these findings as first evidence that investors are more social value-oriented (as opposed to values-oriented) during periods of heightened social concern, as they are increasingly willing to incorporate social considerations into their investment decisions. This behavior may reflect a growing preference for socially responsible investments or a perception

⁹We get similar results when following Pastor and Vorsatz (2020) COVID-19 time window going from February 2020 to May 2020.

¹⁰For ease of readability, we report the coefficients of the interaction with the COVID-19 dummy in Table Appendix E.

that funds with strong social profiles are better positioned to manage long-term risks.

4.2. Intensity of the HCC index

The previous subsection shows that sensitivity to social criteria increases in times of social concern. We further examine how different intensity levels of social concerns (referred to as “shocks”) impact the fund flow sensitivity to social scores. We define four thresholds to characterize the 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 a nonlinear relationship between HCC levels and the flow sensitivity to funds’ social performance (*Soc*). Notably, the sensitivity of fund flows to social performance triples following severe human capital shocks relative to the periods with HCC below the average. By comparison, the effect during Moderate HCC periods is small and not statistically significant, indicating that only extreme social concern episodes meaningfully amplify investors’ responsiveness to social factors. These results suggest that flow sensitivity to social performance intensifies only beyond a certain threshold of human capital concern, reflecting a nonlinear amplification effect. Moving from Columns (1) to (3), we show that the results are robust to the inclusion of controls for fund characteristics and time-fixed effects. Including style-by-time fixed effects, we find that only extremely intense shocks trigger changes in the flow sensitivity to social performance.

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 HCC intensity level. The curves indicate how deviations in the social score are associated with changes in fund flows. While all groups display a

positive association between higher social scores and fund flows, the magnitude of the effect differs substantially across HCC intensity levels. In particular, the effect is modest in periods of very low and low HCC intensity, slightly more pronounced for moderate intensity, and strongest in periods of severe intensity, where an increase of approximately three standard deviations in the social score corresponds to nearly 1 percentage points higher fund flows. This suggests that the sensitivity of investors to social performance increases with the severity of HCC intensity. The substantial increase in flow sensitivity under severe HCC periods suggests that investors consider social performance in all periods, but its influence becomes markedly stronger following extreme social shocks. This threshold effect highlights the context-dependent nature of social risk considerations and underscores the heightened role of social performance during periods of intense social concern.

[Insert Figure 3 about here.]

In addition, fund flow sensitivity towards social scores could vary with the duration of the HCC shocks. The period is considered to contain a shock if the level of the HCC index ranges within the defined intensity range. We consider two duration levels for the shock: a short shock is when the HCC index level goes within the defined 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 Appendix D. We find that the flow sensitivity only increases in times of severe long-lasting shocks.

4.3. Does reallocating capital pay off?

To evaluate whether investors benefit from reallocating capital in response to heightened social concern, we regress future fund returns on the interaction between HCC and the fund's social score. If funds with stronger social performance consistently outperform following periods of elevated HCC, this would indicate that investors who shift their portfolios toward high-social-score funds are making a financially sound decision. In other words, their behavior would reflect rational reallocation based on expected value, suggesting that social indicators become financially material precisely when public concern intensifies. Table 6 presents

the relationship between contemporaneous and future fund returns and sustainability-related variables from period t to $t+5$. We observe that the reallocation of capital toward funds with high social score following periods of heightened social concern, is accompanied by an out-performance of these funds. At time t , the coefficient is negative and statistically significant, suggesting that funds with higher social scores underperform contemporaneously during periods of elevated human capital concern. Beginning at $t+1$, the coefficient turns positive and remains highly significant through $t+3$. By $t+4$, the coefficient becomes economically small and statistically insignificant. This evolution indicates that the initially negative association between social scores and returns reverses in subsequent periods and gradually attenuates over time.

This pattern suggests that investors perceive the social performance of a fund as a financially relevant attribute, leading to increased demand for investment vehicles with strong social profiles. While heightened HCC increases investor awareness of sustainable funds, the persistence of positive subsequent returns indicates that investors are acting in a financially rational manner, reallocating capital based on expected performance rather than attention alone. These findings align with Li et al. (2024), who document that retail investors react to ESG news only when it is financially material, indicating that their ESG-related trading is primarily driven by financial rather than ethical motivations. Our result suggests that the capital reallocation is associated with information that has predictive content for future performance, which is consistent with the value-motivated behavior rather than pure salience or values-based sentiment.

[Insert Table 6 about here.]

Our results show that funds with higher social scores tend to outperform following periods of elevated HCC. This outperformance is particularly pronounced in the short term and fades over time, as indicated by the positive and significant interaction between *HCC* and *Soc*. Several interrelated mechanisms can explain this superior performance. First, a demand-driven channel that arises when investors reallocate capital toward funds with strong social practices, producing persistent net inflows that raise valuations of ESG-intensive holdings and therefore short term returns. We perform a mediation analysis to investigate this demand

channel and to test whether the increased sensitivity to social criterion in times of high HCC affects the future performance of mutual fund through the increase in fund flows. The causal mediation analysis shows that the effect of $HCC \times Soc$ on future fund returns is only partially mediated by fund flows. Although the average causal mediation effect is statistically significant, its small coefficient suggests that only 3% of the total effect is transmitted through fund flows.¹¹

Our findings indicate that the superior performance of funds exhibiting good social score following periods of elevated social concern cannot be fully attributed to capital inflows. This result suggests that the outperformance is not primarily driven by demand pressure but rather by another channel. A second explanation is the fundamental information channel. This mechanism operates when elevated attention to social issues increases the salience and financial materiality of social practices, thereby improving the risk–return profile of firms with strong social performance and, in turn, the portfolios that hold them. This repricing mechanism is consistent with the “green sentiment shock” hypothesis proposed by Pastor et al. (2022). According to their equilibrium framework, shifts in investor preferences toward sustainable assets lead to changes in the perceived discount rates of green versus brown firms, generating temporary valuation gains for environmentally friendly assets when climate concerns intensify. Empirically, they find 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 evidences of this interpretation. Transposed to the social pillar, the post-concern outperformance observed in our study would reflect a sentiment-driven repricing of social risk rather than a pure flow-induced effect.

A final explanation for the outperformance of high-S funds following severe HCC periods would be the managerial skill channel. This mechanism strengthens performance when fund managers are able to interpret and trade on newly relevant social information and deploy incoming flows efficiently across increasingly material ESG opportunity sets. To assess whether the documented return differential reflects capital reallocation rather than asset repricing, we perform a similar analysis on passive index funds and ETFs. Panel A and Panel B of

¹¹See causal mediation results in Appendix Appendix F

Table 7 provide the results for index funds and ETFs respectively. Although none of these funds display an increase in flow sensitivity to social performance in times of social concern,¹² we observe similar return dynamics as for retail funds. Because these index and ETF classes operate under largely passive and flow-insensitive trading rules, their parallel out-performance indicates that price adjustment does not arise from transient demand pressure. Furthermore, because the same temporary outperformance of high-social-score portfolios is observed in these specific asset classes, which do not engage in discretionary stock selection and receive minimal flows, the effect cannot be attributed to fund-level capital movements, manager skill, or screening behavior. Instead, the hump-shaped return pattern reflects a market-wide repricing of social risk that becomes salient following episodes of elevated social concern and subsequently fades as attention normalizes.

[Insert Table 7 about here.]

5. Corroborating Results

These results are consistent with a shift in sensitivity to social performance during periods in which the materiality of social factors becomes salient. This pattern suggests that retail investors' responses to social performance are at least partly driven by financial considerations. In this section, we provide additional evidence supporting this interpretation.

5.1. Retail versus institutional investors

We first examine whether the documented time variation in flow sensitivity to social performance is unique to retail investors. To do so, we investigate institutional investors' consideration of social performance along our *HCC* index. This distinction is valuable because retail and institutional investors differ in several key ways, and those differences significantly shape their demand for sustainable investments. While retail investors enjoy greater autonomy in expressing ethical preferences, institutional investors are constrained by fiduciary duties, strategic ESG policies, or explicit sustainability mandates. These constraints restrict the universe of stocks they can hold and limit the volatility of their trading

¹²Results on the flow sensitivity to social performance of index funds and ETFs are available in Appendix Appendix G.

activity over time. All of this makes institutional investors less likely to adapt their consideration of investment’s social performance according to the level of social concern in the economy. Therefore, we expect little or no reaction of institutional fund flows to our HCC index as compared to retails.

Table 8 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. Contrary to 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 specific to retail investors.

[Insert Table 8 about here.]

5.2. Sensitivity to HCC validation

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.

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), and the Economic Policy Uncertainty (EPU) 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 9). This robustness

test confirms that the relationship between attention to human capital concerns 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.

[Insert Table 9 about here.]

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 1000 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 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 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.

5.3. Alternative concern index: The human rights and individual freedom index

To further understand the motivations of retail investors to reallocate capital following periods of elevated social concern, we construct an alternative index capturing media coverage of ethical issues. Following the methodology used for the HCC index, we replace the corpus of human capital-related news articles with articles from the "human rights and individual freedoms" category. Although these issues are also part of the SASB Materiality Map under the Social Capital category, they are generally considered less directly material to firm fundamentals and financial performance. Given the risk captured by our social performance measure and the low materiality of the concerns reflected in this Human Rights Concern (HRC) index, we would expect no reaction from investors who integrate sustainability primarily for financial purposes. Conversely, a significant reaction from retail investors would suggest that they do not differentiate by materiality when incorporating social performance into their investment decisions, indicating some ethical motivation.

[Insert Table 10 about here.]

We re-estimate our baseline regression, replacing our HCC index with this novel values-oriented HRC index and we find no significant effect on fund flow sensitivity to social risk scores. Table 10 shows the results. The lack of investor responsiveness during periods of heightened human rights or civil liberties concern suggests that these issues may be perceived as more ideologically driven or less financially material to the average firm's operations. Specifically, investors do not adjust their consideration of social risk metrics in response to periods of heightened ethical concern. This absence of response contrasts with the results obtained using the *HCC* index and reinforces the interpretation that retail investors primarily value the social performance of their investments for financial risk management purposes rather than for ethical considerations.

5.4. Sustainability risk assessment versus sustainability labels

Finally, a potential alternative explanation is that the stronger flow sensitivity to social scores following high-HCC periods reflects heightened salience of social issues rather than

genuine financial materiality. We argue, both conceptually and empirically, that salience and financial materiality are not competing explanations but rather complementary mechanisms. Media coverage of human capital issues makes financially relevant social risks more visible, thereby drawing investors' limited attention to factors that affect expected cash flows and firm resilience. In this sense, salience acts as a transmission channel through which financially material information becomes incorporated into investment decisions.

To further support our interpretation of the results, we examine whether the increased sensitivity to social performance reflects a response to risk-relevant information or to sustainability labeling. We replace the social risk score with a dummy indicating whether the fund's name includes ESG-related terms. If the observed increase in flow sensitivity reflects a risk-hedging motive, we should observe no significant response when relying solely on the ESG label, as it does not convey information about the fund's underlying ESG risk exposures. In contrast, a similar reaction to the ESG label would suggest a preference-driven channel rather than a risk-based explanation. To test this, we re-estimate Equation 5, introducing a dummy variable, *ESG Name*, equal to 1 if the fund name includes sustainability-related terms and 0 otherwise. Table 11 presents the results.

[Insert Table 11 about here.]

The estimates reveal a clear distinction between risk-based social information and a simple sustainability label. While fund flows respond positively to both metrics in general, the interaction with HCC differs significantly. In contrast to social risk scores, ESG labels do not become more attractive during periods of heightened social concern. Specifically, a one standard deviation increase in HCC completely reverses the consideration of the ESG label. In comparison, the sensitivity to social risk score increases by 50-60%. These findings imply that investors respond not merely to the visibility of social issues but to the recognition of their financial relevance, confirming that the observed reallocation of capital is primarily value-motivated rather than values-driven. The contrast in reaction reinforces the financially motivated, risk-hedging interpretation of our results. Investors target social performance to mitigate exposure when social risk materializes, rather than responding to simple sustainability claims.

6. Conclusion

We study how retail investors incorporate the social dimension of ESG into their investment decisions by constructing a novel Human Capital Concern (HCC) index that captures shifts in media attention to financially material labor- and workforce-related risks. We show that retail mutual fund flows become more sensitive to funds’ social risk scores when human capital concerns are elevated. This sensitivity is highly nonlinear and concentrated in periods of severe and persistent episodes. In contrast, we observe no comparable response when public attention centers on human-rights or values-oriented issues that are less clearly tied to firm fundamentals. We further document that high-social-score funds subsequently outperform following high-HCC periods, and that this return differential is consistent with a repricing of social risk rather than temporary demand pressure.

Taken together, our results suggest that retail investors pay closer attention to social performance when social risks become financially salient, consistent with the presence of value-motivated behavior, rather than when it reflects purely ethical or prosocial considerations. Importantly, our results do not rule out the presence of non-pecuniary or values-driven motives; rather, they indicate that such motives alone cannot explain the state-dependent nature of capital reallocation we document. This evidence adds nuance to the broader debate on value- versus values-driven sustainable investing by showing that the relevance of social factors for retail capital flows is state-dependent and arises particularly when social risks become salient. More broadly, our findings highlight that social issues which was long considered as the “quiet pillar” of ESG, can influence asset allocation and expected returns 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, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. *Quarterly Journal of Economics* 131, 1593–1636.
- Barber, B.M., Morse, A., Yasuda, A., 2021. Impact investing. *Journal of Financial Economics* 139, 162–185.
- 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.
- 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.
- 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.
- Døskeland, T., Pedersen, L.J.T., 2016. Investing with brain or heart? a field experiment on responsible investment. *Management Science* 62, 1632–1644.
- 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., Stroebe, 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.
- 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.
- Gutsche, G., Ziegler, A., 2019. Which private investors are willing to pay for sustainable investments? empirical evidence from stated choice experiments. *Journal of Banking & Finance* 102, 193–214.
- 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* .
- 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 concerns

This table reports the results of regression analyzing the flow-performance sensitivity in times of social concerns. 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. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	<i>Dependent variable: Net Flow (%)</i>				
	(1)	(2)	(3)	(4)	(5)
Return _{<i>t</i>-1}	0.355*** (0.012)	0.361*** (0.012)	0.353*** (0.014)	0.352*** (0.014)	0.361*** (0.015)
Star _{<i>t</i>-1}	0.694*** (0.013)	0.695*** (0.013)	0.689*** (0.013)	0.690*** (0.013)	0.709*** (0.014)
Log(Age) _{<i>t</i>-1}	-0.296*** (0.022)	-0.302*** (0.022)	-0.303*** (0.022)	-0.304*** (0.022)	-0.307*** (0.014)
Log(Size) _{<i>t</i>-1}	-0.416*** (0.016)	-0.411*** (0.016)	-0.416*** (0.016)	-0.417*** (0.016)	-0.418*** (0.016)
Flow _{<i>t</i>-1} (%)	1.330*** (0.017)	1.336*** (0.017)	1.322*** (0.017)	1.322*** (0.017)	1.321*** (0.017)
Env _{<i>t</i>-1}	-0.063*** (0.016)	-0.028* (0.015)	-0.063*** (0.017)	-0.078*** (0.018)	-0.089*** (0.019)
Soc _{<i>t</i>-1}	0.071*** (0.016)	0.059*** (0.015)	0.048*** (0.017)	0.073*** (0.018)	0.078*** (0.019)
HCC _{<i>t</i>-1} × Soc _{<i>t</i>-1}	0.024* (0.012)	0.031** (0.012)	0.026* (0.015)	0.042*** (0.016)	0.047*** (0.018)
HCC _{<i>t</i>-1} × Return _{<i>t</i>-1}					0.019 (0.015)
HCC _{<i>t</i>-1} × Star _{<i>t</i>-1}					0.129*** (0.013)
HCC _{<i>t</i>-1} × Env _{<i>t</i>-1}					0.002 (0.018)
Observations	263,519	263,519	263,519	263,519	263,519
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
Residual Std. Error	6.018	6.002	5.995	5.995	5.994
F Statistic	761.303***	136.650***	17.734***	17.732***	17.744***

Table 5: Shock intensity

This table reports the results of regression analyzing the flow-performance sensitivity in times of social concerns 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. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	<i>Dependent variable: Net flow (%)</i>		
	(1)	(2)	(3)
Return _{<i>t</i>-1}	0.360*** (0.013)	0.360*** (0.013)	0.358*** (0.014)
Star _{<i>t</i>-1}	0.700*** (0.014)	0.697*** (0.014)	0.692*** (0.014)
Log(Age) _{<i>t</i>-1}	-0.301*** (0.022)	-0.302*** (0.022)	-0.304*** (0.022)
Log(Size) _{<i>t</i>-1}	-0.411*** (0.015)	-0.411*** (0.015)	-0.416*** (0.016)
Flow _{<i>t</i>-1} (%)	1.334*** (0.017)	1.248*** (0.017)	1.236*** (0.017)
Env _{<i>t</i>-1}	-0.050*** (0.016)	-0.053*** (0.016)	-0.088*** (0.019)
Soc _{<i>t</i>-1}	0.056*** (0.019)	0.060*** (0.019)	0.061*** (0.023)
Moderate HCC _{<i>t</i>-1} × Soc _{<i>t</i>-1}	0.020 (0.026)	0.019 (0.026)	-0.008 (0.035)
Severe HCC _{<i>t</i>-1} × Soc _{<i>t</i>-1}	0.118*** (0.036)	0.114*** (0.035)	0.120*** (0.045)
Observations	263,519	263,519	263,519
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
Residual Std. Error	6.017	6.002	5.995
F Statistic	810.316***	130.668***	17.664***

Table 6: Return predictability

This table reports regression results for fund returns at horizons t to $t + 5$. The dependent variable is the fund return at each horizon. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	<i>Dependent variable: Return</i>					
	Return _{t}	Return _{$t+1$}	Return _{$t+2$}	Return _{$t+3$}	Return _{$t+4$}	Return _{$t+5$}
Star _{t}	0.142*** (0.005)	0.163*** (0.005)	0.007 (0.005)	0.011** (0.005)	0.009* (0.005)	0.003 (0.005)
Log(Age _{t})	0.098*** (0.008)	0.105*** (0.008)	0.061*** (0.008)	0.063*** (0.008)	0.058*** (0.008)	0.061*** (0.008)
Log(Size _{t})	0.006 (0.006)	-0.31*** (0.006)	0.030*** (0.006)	0.030*** (0.006)	0.028*** (0.006)	0.031*** (0.006)
Flow _{t}	0.158*** (0.006)	-0.021*** (0.006)	0.001 (0.006)	-0.002 (0.006)	-0.007 (0.006)	0.006 (0.006)
Soc _{t}	-0.034*** (0.007)	-0.026*** (0.007)	-0.007 (0.007)	-0.007 (0.007)	-0.101*** (0.007)	-0.121*** (0.007)
Env _{t}	-0.007 (0.007)	-0.005 (0.007)	-0.024*** (0.007)	-0.027*** (0.007)	0.072*** (0.007)	0.069*** (0.007)
HCC $\times$ Soc _{t}	-0.027*** (0.006)	0.047*** (0.006)	0.091*** (0.006)	0.083*** (0.006)	0.008 (0.007)	-0.001 (0.007)
HCC $\times$ Env _{t}	-0.014** (0.006)	-0.020*** (0.006)	-0.111*** (0.007)	-0.118*** (0.007)	0.034*** (0.007)	0.040*** (0.007)
Observations	263,519	263,519	259,667	255,831	252,024	248,234
Style $\times$ Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Covid	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.822	0.822	0.821	0.822	0.822	0.823
Adjusted R ²	0.822	0.821	0.820	0.822	0.821	0.822
Residual Std. Error	2.137	2.140	2.151	2.149	2.159	2.156
F Statistic	1,354.175***	1,343.272***	1,328.181***	1,337.017***	1,327.954***	1,332.120***

Table 7: Performance of passive investment funds

This table reports regression results for fund returns at horizons t to $t + 5$. 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. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Index Funds						
	<i>Dependent variable: Return</i>					
	Return _{t}	Return _{$t+1$}	Return _{$t+2$}	Return _{$t+3$}	Return _{$t+4$}	Return _{$t+5$}
Soc _{t}	0.013 (0.012)	0.062*** (0.012)	0.065*** (0.012)	0.055*** (0.012)	-0.002 (0.012)	-0.048*** (0.013)
HCC _{t} $\times$ Soc _{t}	-0.054*** (0.011)	0.055*** (0.012)	0.081*** (0.012)	0.038*** (0.012)	0.030 (0.011)	-0.007 (0.011)
Observations	98,169	98,169	96,661	95,160	93,675	92,194
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Style $\times$ Time FE	Yes	Yes	Yes	Yes	Yes	Yes
COVID-19	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.793	0.787	0.787	0.789	0.789	0.789
Adjusted R ²	0.791	0.785	0.785	0.787	0.787	0.787
Residual Std. Error	2.474	2.500	2.509	2.503	2.508	2.510
F Statistic	413.306***	400.120***	396.830***	399.848***	398.440***	396.125***
Panel B: Exchange-Traded Funds						
	<i>Dependent variable: Return</i>					
	Return _{t}	Return _{$t+1$}	Return _{$t+2$}	Return _{$t+3$}	Return _{$t+4$}	Return _{$t+5$}
Soc _{t}	0.045*** (0.015)	0.088*** (0.015)	0.095*** (0.015)	0.081*** (0.016)	0.031** (0.016)	-0.013 (0.016)
HCC _{t} $\times$ Soc _{t}	-0.060*** (0.014)	0.062*** (0.015)	0.070*** (0.015)	0.031*** (0.015)	0.025* (0.015)	-0.010 (0.015)
Observations	68,966	68,966	67,757	66,566	65,391	64,225
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Style $\times$ Time FE	Yes	Yes	Yes	Yes	Yes	Yes
COVID-19	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.754	0.747	0.746	0.748	0.748	0.748
Adjusted R ²	0.751	0.743	0.743	0.744	0.745	0.745
Residual Std. Error	2.784	2.818	2.831	2.825	2.830	2.833
F Statistic	231.979***	222.923***	220.297***	220.792***	219.500***	217.859***

Table 8: Flow-social performance sensitivity of institutional investors

This table reports the results of regression analysis of the flow-performance sensitivity in times of social concerns. 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. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	<i>Dependent variable: Net flow (%)</i>	
	(1)	(2)
Return _{<i>t</i>-1}	0.307*** (0.020)	0.307*** (0.020)
Star _{<i>t</i>-1}	1.067*** (0.018)	1.043*** (0.017)
Log(Age) _{<i>t</i>-1}	-0.530*** (0.029)	-0.526*** (0.029)
Log(Size) _{<i>t</i>-1}	-0.786*** (0.019)	-0.785*** (0.019)
Flow _{<i>t</i>-1} (%)	1.804*** (0.019)	1.805*** (0.019)
Env _{<i>t</i>-1}	-0.104*** (0.027)	-0.129*** (0.025)
Soc _{<i>t</i>-1}	0.142*** (0.026)	0.103*** (0.031)
HCC _{<i>t</i>-1} × Soc _{<i>t</i>-1}	0.035 (0.024)	
Moderate HCC × Soc _{<i>t</i>-1}		0.101** (0.047)
Severe HCC × Soc _{<i>t</i>-1}		0.131** (0.062)
Observations	210,778	210,778
Style x Time FE	Yes	Yes
COVID	Yes	Yes
R ²	0.097	0.096
Adjusted R ²	0.093	0.092
Residual Std. Error	7.221	7.222
F Statistic	24.781***	24.750***

Table 9: 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 * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	<i>Dependent variable: Net Flow (%)</i>	
	HCC (1)	Residualized HCC (2)
Return _{<i>t</i>-1}	0.361*** (0.015)	0.362*** (0.015)
Star _{<i>t</i>-1}	0.709*** (0.014)	0.695*** (0.014)
Log(Age) _{<i>t</i>-1}	-0.307*** (0.014)	-0.306*** (0.022)
Log(Size) _{<i>t</i>-1}	-0.418*** (0.016)	-0.416*** (0.016)
Flow _{<i>t</i>-1} (%)	1.321*** (0.017)	1.322*** (0.017)
Env _{<i>t</i>-1}	-0.089*** (0.019)	-0.085*** (0.019)
Soc _{<i>t</i>-1}	0.078*** (0.019)	0.075*** (0.019)
HCC _{<i>t</i>-1} × Soc _{<i>t</i>-1}	0.047*** (0.018)	0.253** (0.107)
HCC _{<i>t</i>-1} × Return _{<i>t</i>-1}	0.019 (0.015)	0.359*** (0.083)
HCC _{<i>t</i>-1} × Star _{<i>t</i>-1}	0.129*** (0.013)	0.432*** (0.075)
HCC _{<i>t</i>-1} × Env _{<i>t</i>-1}	0.002 (0.018)	0.025 (0.108)
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
Residual Std. Error	5.994	5.994
F Statistic	17.744***	17.688***

Table 10: Flow-social performance sensitivity along Human Rights and Individual Freedom concerns

This table reports the results of regression analyzing the flow-performance sensitivity in times of social concerns 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. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	<i>Dependent variable: Net flow (%)</i>			
	(1)	(2)	(3)	(4)
Return _{t-1}	0.354*** (0.012)	0.360*** (0.012)	0.353*** (0.014)	0.358*** (0.014)
Star _{t-1}	0.693*** (0.013)	0.694*** (0.013)	0.689*** (0.013)	0.691*** (0.014)
Log(Age) _{t-1}	-0.296*** (0.022)	-0.302*** (0.022)	-0.304*** (0.022)	-0.305*** (0.022)
Log(Size) _{t-1}	-0.413*** (0.015)	-0.409*** (0.015)	-0.415*** (0.016)	-0.415*** (0.016)
Flow _{t-1} (%)	1.330*** (0.017)	1.337*** (0.017)	1.322*** (0.017)	1.322*** (0.017)
Env _{t-1}	-0.067*** (0.016)	-0.029* (0.015)	-0.063*** (0.017)	-0.83*** (0.018)
Soc _{t-1}	0.072*** (0.015)	0.059*** (0.015)	0.050*** (0.017)	0.074*** (0.018)
HRC _{t-1} × Soc _{t-1}	0.015 (0.013)	0.020 (0.013)	0.014 (0.016)	0.005 (0.016)
HRC _{t-1} × Return _{t-1}	0.019 (0.013)	0.012 (0.013)	0.013 (0.015)	0.010 (0.015)
HRC _{t-1} × Star _{t-1}	0.006 (0.013)	0.006 (0.013)	0.006 (0.013)	0.005 (0.013)
HRC _{t-1} × Env _{t-1}	-0.023* (0.014)	-0.020 (0.014)	-0.020 (0.016)	-0.015 (0.016)
Observations	263,519	263,519	263,519	263,519
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
Residual Std. Error	6.018	6.002	5.995	5.995
F Statistic	646.648***	132.861***	17.674***	17.617***

Table 11: Social Risk Score versus ESG Name

This table reports the results of regression analyzing the flow-performance sensitivity in times of social concerns. 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. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	<i>Dependent variable: Net Flow</i>		
Return _{<i>t</i>-1}	0.353*** (0.014)	0.351*** (0.014)	0.351*** (0.014)
Star _{<i>t</i>-1}	0.688*** (0.013)	0.689*** (0.013)	0.689*** (0.013)
Log(Age) _{<i>t</i>-1}	-0.301*** (0.022)	-0.301*** (0.022)	-0.301*** (0.022)
Log(Size) _{<i>t</i>-1}	-0.412*** (0.016)	-0.414*** (0.016)	-0.414*** (0.016)
Flow _{<i>t</i>-1} (%)	1.321*** (0.017)	1.320*** (0.017)	1.320*** (0.017)
Soc _{<i>t</i>-1}	0.043** (0.017)	0.072*** (0.019)	0.070*** (0.019)
Env _{<i>t</i>-1}	-0.061*** (0.017)	-0.088*** (0.019)	-0.088*** (0.019)
ESG_Name	0.224*** (0.080)	0.220*** (0.080)	0.173** (0.087)
HCC _{<i>t</i>-1} × ESG_Name	-0.173** (0.079)	-0.188** (0.079)	-0.177** (0.085)
HCC _{<i>t</i>-1} × Soc _{<i>t</i>-1}		0.044** (0.018)	0.045** (0.018)
HCC _{<i>t</i>-1} × Env _{<i>t</i>-1}		0.010 (0.018)	0.010 (0.018)
Soc _{<i>t</i>-1} × ESG_Name			0.132 (0.094)
HCC _{<i>t</i>-1} × ESG_Name × HCC _{<i>t</i>-1}			-0.042 (0.095)
Observations	263,519	263,519	263,519
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 plots 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.

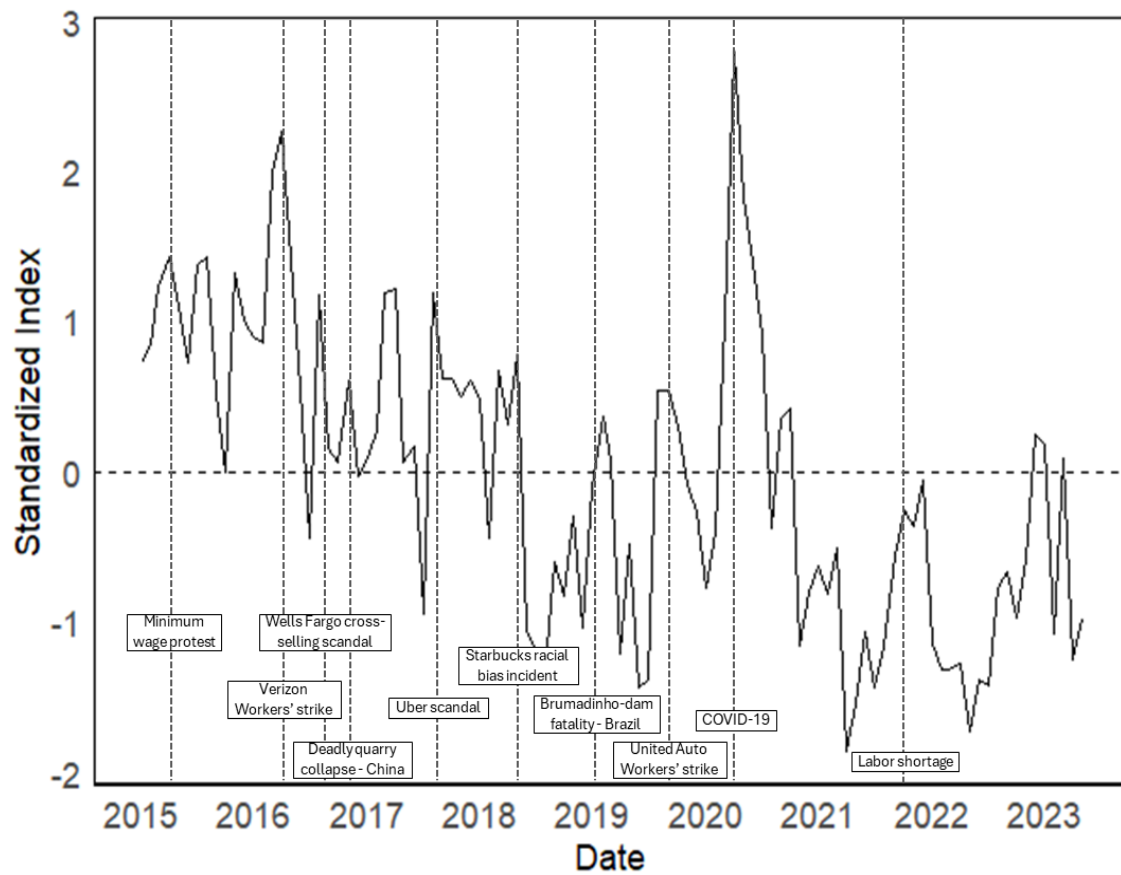


Figure 2: Flow-performance sensitivity per quartiles of HCC

The figure reports average values of the flow-performance sensitivity of retail investors, along with 95% confidence intervals, by quintiles 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.

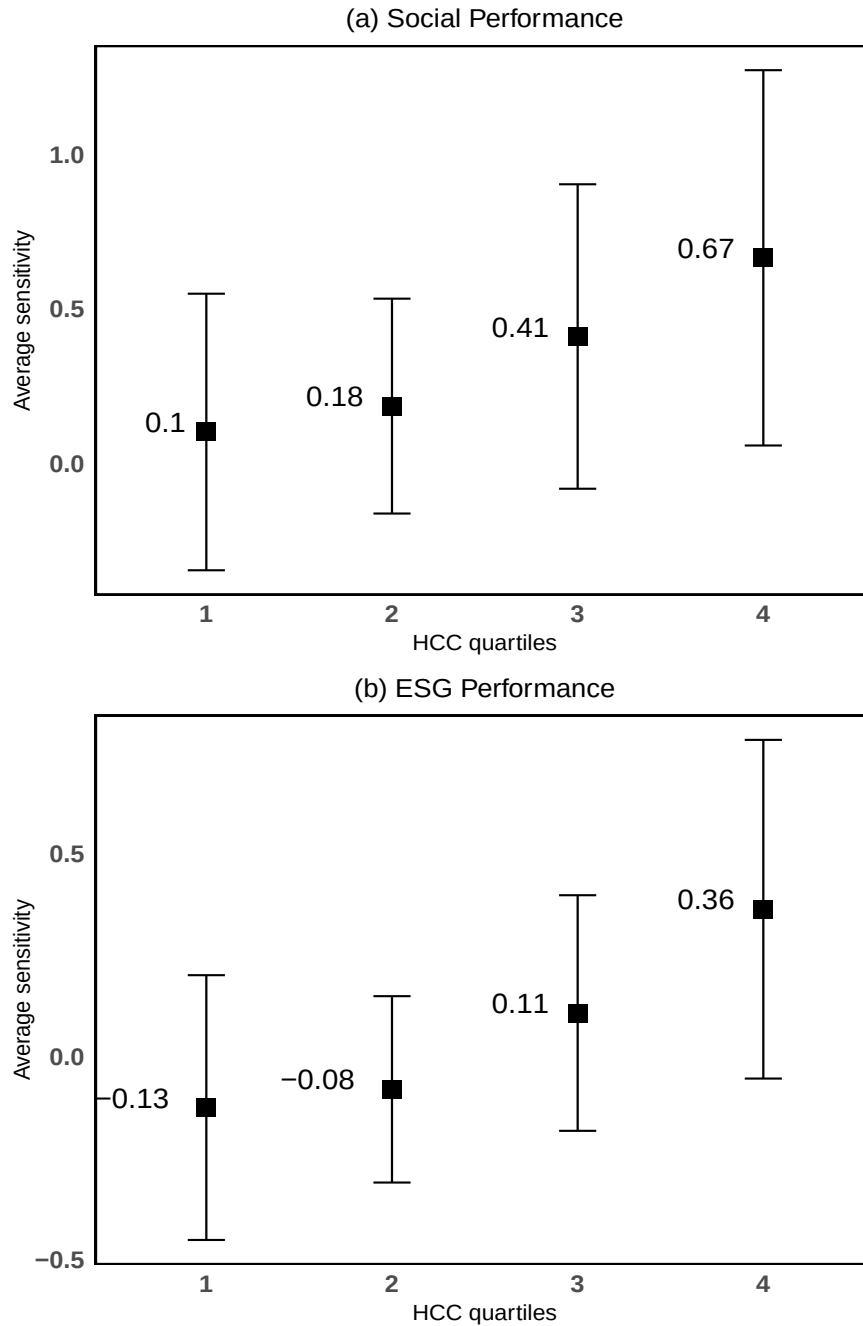


Figure 3: Generalized Additive Model regression - HCC intensity

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.

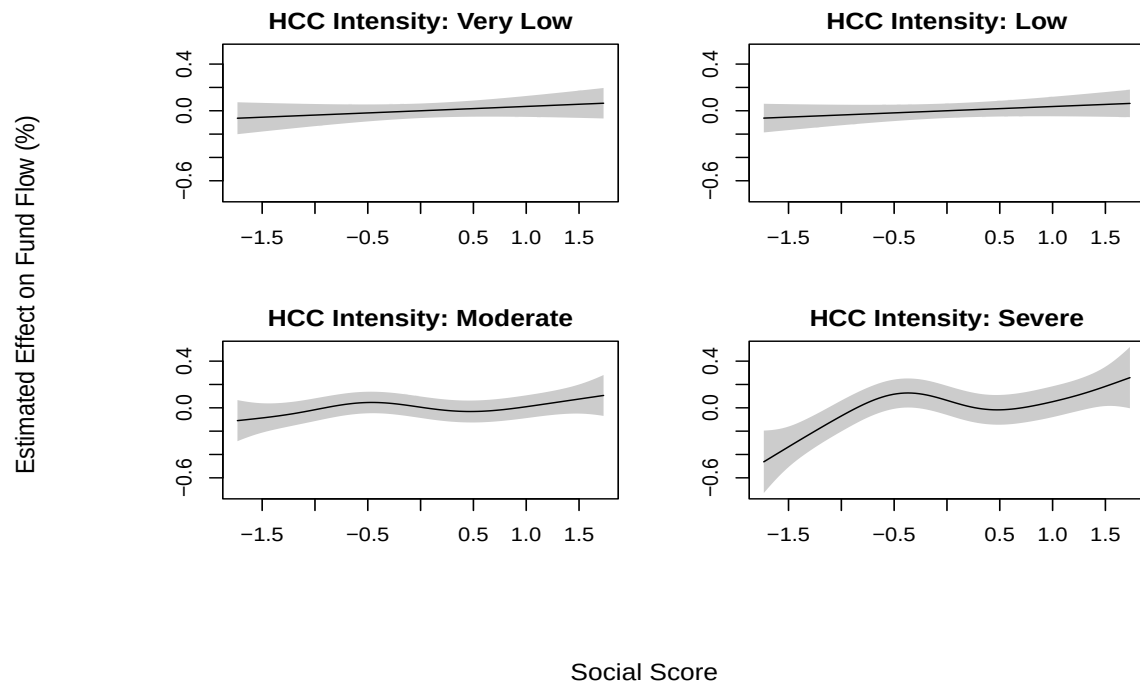
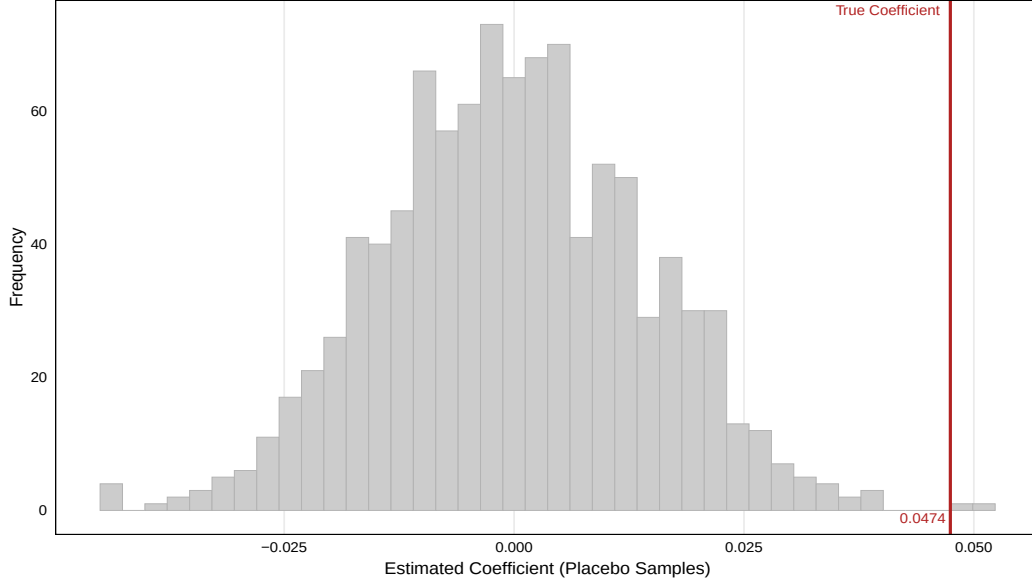


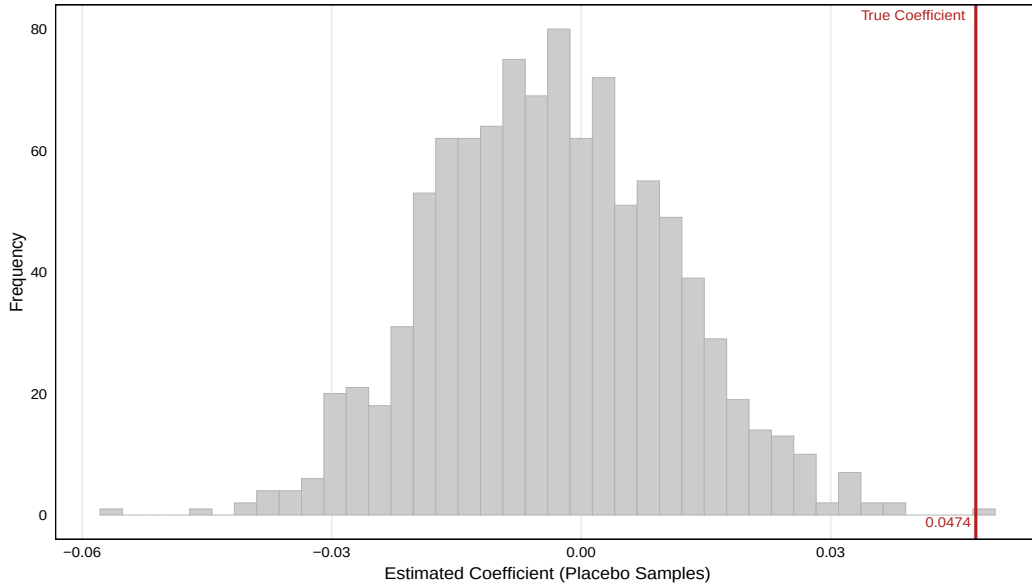
Figure 4: Placebo distribution of $HCC \times Soc$ coefficients

This figure plots 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



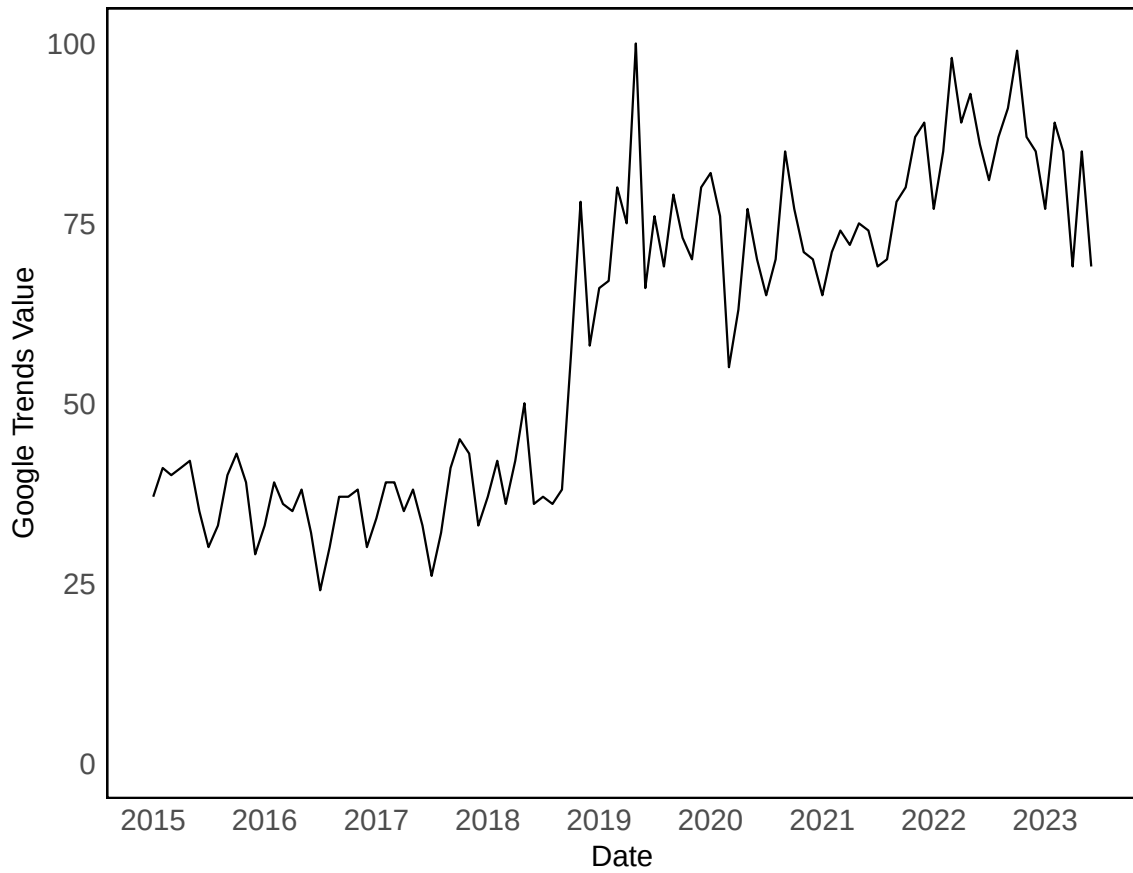
Panel B: Random Date Permutation by Fund



Appendix A. Google Trends on “Human Capital” topic

Figure A.5: This figure displays Google Trends data for the topic “Human Capital” from January 2015 to June 2023. The graph shows a gradual increase in search interest, with a sharp rise around 2020, followed by fluctuations at relatively high levels. See the trends data at:

<https://trends.google.fr/trends/explore?date=2010-01-01%202025-03-04&q=%2Fm%2F0cf65&hl=en>



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), and the Economic Policy Uncertainty (EPU) index.¹³ 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.12: Regression of monthly changes in HCC on macro variables

Variable	Coefficient	Std. Error	t-statistic	p-value
Intercept	-0.00411	0.0155	-0.265	0.792
Δ Unemployment Rate	0.0411	0.0194	2.12	0.037
Δ VIX	0.00425	0.00385	1.10	0.273
Δ CPI	-0.00199	0.0452	-0.044	0.965
Δ EPU	0.000157	0.000508	0.309	0.758
R^2		0.105		
Adjusted- R^2		0.068		
Observations		N = 101		

The regression results indicate that the model only explains about 10.5% of the monthly variation in HCC ($R^2 = 0.105$). 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 0.041 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.

¹³All macroeconomic variables (UNRATE, VIXCLS, CPALTT01USM657N, and USEPUINDXD) are retrieved from <https://fred.stlouisfed.org/>.

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. Duration of HCC

Table D.13: 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. *Sust* is either social score (Columns 1 to 3) or ESG score (Columns 4 to 6). All variables are standardized. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	<i>Dependent variable: Net Flow (%)</i>					
	Social			ESG		
	Low (1)	Moderate (2)	Severe (3)	Low (4)	Moderate (5)	Severe (6)
Return _{<i>t</i>-1}	0.359*** (0.014)	0.358*** (0.014)	0.358*** (0.014)	0.376*** (0.014)	0.377*** (0.014)	0.376*** (0.014)
Star _{<i>t</i>-1}	0.691*** (0.014)	0.692*** (0.014)	0.692*** (0.014)	0.697*** (0.014)	0.697*** (0.014)	0.697*** (0.014)
Log(Age) _{<i>t</i>-1}	-0.304*** (0.022)	-0.304*** (0.022)	-0.304*** (0.022)	-0.299*** (0.022)	-0.299*** (0.022)	-0.298*** (0.022)
Log(Size) _{<i>t</i>-1}	-0.415*** (0.016)	-0.415*** (0.016)	-0.416*** (0.016)	-0.426*** (0.015)	-0.426*** (0.015)	-0.426*** (0.015)
Flow _{<i>t</i>-1} (%)	1.322*** (0.017)	1.322*** (0.017)	1.322*** (0.017)	1.352*** (0.016)	1.352*** (0.016)	1.352*** (0.016)
Env _{<i>t</i>-1}	-0.080*** (0.018)	-0.082*** (0.018)	-0.088*** (0.018)			
Soc _{<i>t</i>-1}	0.074*** (0.021)	0.086*** (0.021)	0.059*** (0.019)			
ESG _{<i>t</i>-1}				0.014 (0.018)	-0.000 (0.019)	-0.011 (0.017)
Long Shock × Sust _{<i>t</i>-1}	0.004 (0.035)	-0.029 (0.033)	0.154*** (0.047)	-0.039*** (0.034)	0.009 (0.032)	0.134*** (0.043)
Short Shock × Sust _{<i>t</i>-1}	-0.355*** (0.162)	-0.331** (0.163)	-0.006 (0.091)	-0.201 (0.155)	-0.046 (0.142)	-0.068 (0.087)
Observations	263,519	263,519	263,519	274,196	274,196	274,196
Style × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.057	0.57	0.057	0.058	0.058	0.058
Adjusted R ²	0.054	0.054	0.054	0.055	0.055	0.055
Residual Std. Error	5.995	5.995	5.995	6.047	6.047	6.047
F Statistic	17.660***	17.660***	17.667***	18.817***	18.813***	18.826***

Appendix E. COVID-19 period - Full Table

Table E.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.

	<i>Dependent variable: Net Flow (%)</i>			
	(1)	(2)	(3)	(4)
Return _{t-1}	0.354*** (0.014)	0.361*** (0.015)	0.378*** (0.014)	0.378*** (0.014)
Star _{t-1}	0.698*** (0.013)	0.709*** (0.014)	0.701*** (0.013)	0.712*** (0.014)
Log(Age) _{t-1}	-0.306*** (0.022)	-0.307*** (0.022)	-0.300*** (0.022)	-0.300*** (0.022)
Log(Size) _{t-1}	-0.417*** (0.016)	-0.418*** (0.016)	-0.427*** (0.015)	-0.427*** (0.015)
Flow _{t-1} (%)	1.321*** (0.017)	1.321*** (0.017)	1.351*** (0.016)	1.351*** (0.016)
Env _{t-1}	-0.058*** (0.017)	-0.089*** (0.019)		
Soc _{t-1}	0.043** (0.017)	0.078*** (0.019)		
ESG _{t-1}			-0.002 (0.015)	0.005 (0.015)
HCC _{t-1} × Return _{t-1}	0.013 (0.014)	0.019 (0.015)	0.013 (0.014)	0.011 (0.015)
HCC _{t-1} × Star _{t-1}	0.121*** (0.013)	0.129*** (0.013)	0.109*** (0.013)	0.118*** (0.013)
HCC _{t-1} × Env _{t-1}	0.029* (0.017)	0.002 (0.018)		
HCC _{t-1} × Soc _{t-1}	0.018** (0.017)	0.047*** (0.018)		
HCC _{t-1} × ESG _{t-1}			0.035** (0.015)	0.040*** (0.015)
Return _{t-1} × COVID _t		-0.132*** (0.065)		0.020 (0.057)
Star _{t-1} × COVID _t		-0.151*** (0.055)		-0.147*** (0.049)
Env _{t-1} × COVID _t		0.137** (0.063)		
Soc _{t-1} × COVID _t		-0.228*** (0.059)		
ESG _{t-1} × 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 F. Mediation analysis

Table F.15: 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

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

Table G.16: Flow sensitivity to social performance in times of HCC

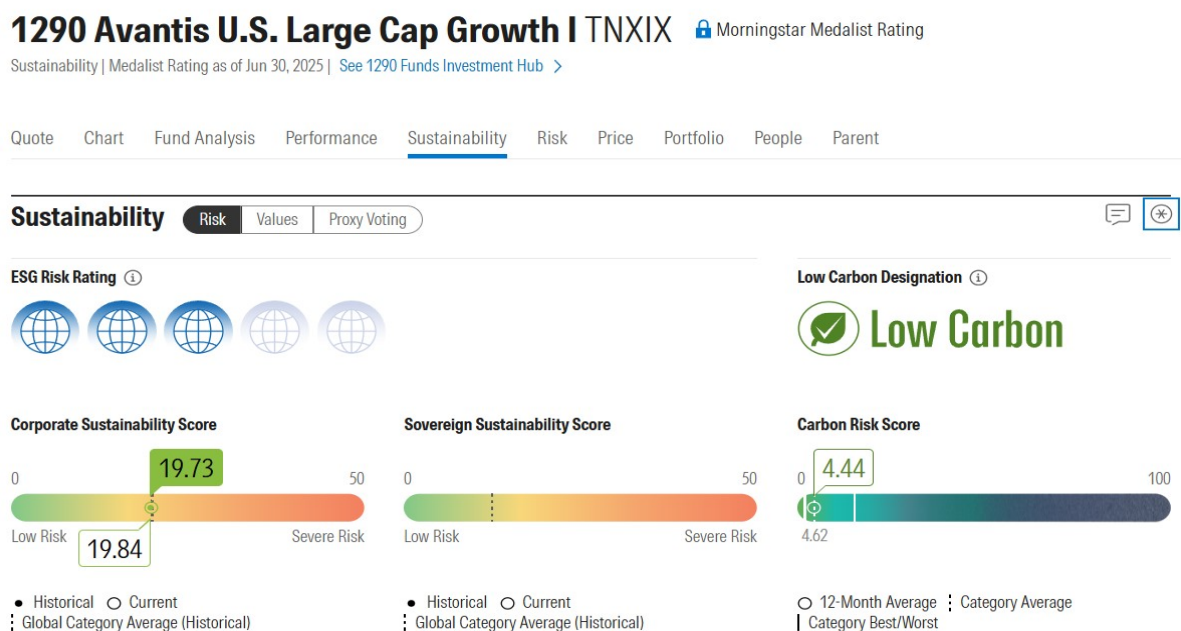
This table reports regression results analyzing the flow sensitivity to social performance along the level of HCC. Columns (1) and (2) correspond to index funds and ETFs sample, respectively. All variables are standardized. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels,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

	Index Funds	ETFs
<i>Dependent variable: Net Flow (%)</i>		
Return _{t-1}	1.012*** (0.029)	1.069*** (0.032)
Star _{t-1}	0.493*** (0.029)	0.588*** (0.033)
Log(Age) _{t-1}	-0.839*** (0.053)	-0.802*** (0.074)
Log(Size) _{t-1}	-0.413*** (0.034)	-0.442*** (0.048)
Flow _{t-1} (%)	0.937*** (0.026)	1.171*** (0.031)
Soc _{t-1}	0.068* (0.040)	-0.054 (0.046)
Env _{t-1}	-0.136*** (0.039)	-0.176*** (0.045)
HCC _{t-1} × Return _{t-1}	0.045 (0.029)	0.081** (0.032)
HCC _{t-1} × Star _{t-1}	-0.066** (0.028)	-0.072** (0.031)
HCC _{t-1} × Env _{t-1}	0.035 (0.036)	0.035 (0.042)
HCC _{t-1} × Soc _{t-1}	0.049 (0.038)	0.046 (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
Residual Std. Error	8.114 (df = 97,263)	8.370 (df = 68,060)
F Statistic	8.379*** (df = 905; 97,263)	7.979*** (df = 905; 68,060)

Appendix H. 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 H.6: 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 H.17 presents the baseline and intensity results. Figure H.7 displays the estimated smooth effects of ESG score on fund net flows across four groups defined by varying levels of HCC intensity.

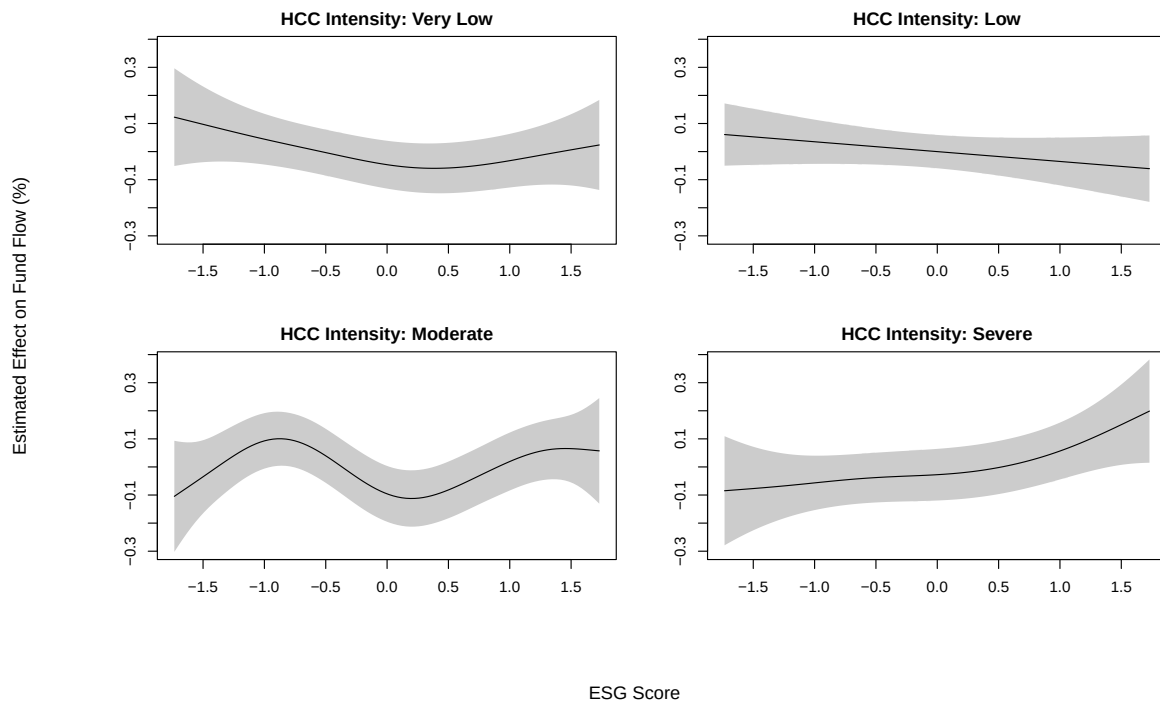
Table H.17: Flow-ESG performance sensitivity along social concerns

This table reports the results of regression analyzing the flow-sustainable performance sensitivity in times of social concerns. 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				
	<i>Dependent variable: Net Flow (%)</i>			
	(1)	(2)	(3)	(4)
Return _{t-1}	0.380*** (0.012)	0.381*** (0.012)	0.378*** (0.014)	0.378*** (0.014)
Star _{t-1}	0.705*** (0.013)	0.705*** (0.013)	0.701*** (0.013)	0.712*** (0.014)
Log(Age) _{t-1}	-0.293*** (0.022)	-0.297*** (0.021)	-0.300*** (0.022)	-0.300*** (0.022)
Log(Size) _{t-1}	-0.427*** (0.015)	-0.422*** (0.015)	-0.427*** (0.015)	-0.427*** (0.015)
Flow _{t-1} (%)	1.360*** (0.016)	1.365*** (0.016)	1.351*** (0.016)	1.351*** (0.016)
ESG _{t-1}	-0.013 (0.014)	0.029** (0.012)	-0.002 (0.015)	0.005 (0.015)
HCC _{t-1} × ESG _{t-1}	0.040*** (0.012)	0.036*** (0.012)	0.035** (0.015)	0.040*** (0.015)
HCC _{t-1} × Return _{t-1}	0.027** (0.012)	0.031** (0.012)	0.013 (0.014)	0.011 (0.015)
HCC _{t-1} × Star _{t-1}	0.106*** (0.012)	0.111*** (0.012)	0.109*** (0.013)	0.118*** (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				
	<i>Dependent variable: Net Flow (%)</i>			
	(1)	(2)	(3)	(4)
ESG _{t-1}	0.003 (0.016)	-0.039** (0.018)	-0.033* (0.018)	-0.004 (0.020)
Moderate HCC _{t-1} × ESG _{t-1}	0.036 (0.028)	0.040 (0.028)	0.040 (0.028)	-0.025 (0.035)
Severe HCC _{t-1} × ESG _{t-1}	0.090*** (0.033)	0.102*** (0.033)	0.102*** (0.033)	0.074* (0.040)
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 H.7: 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.

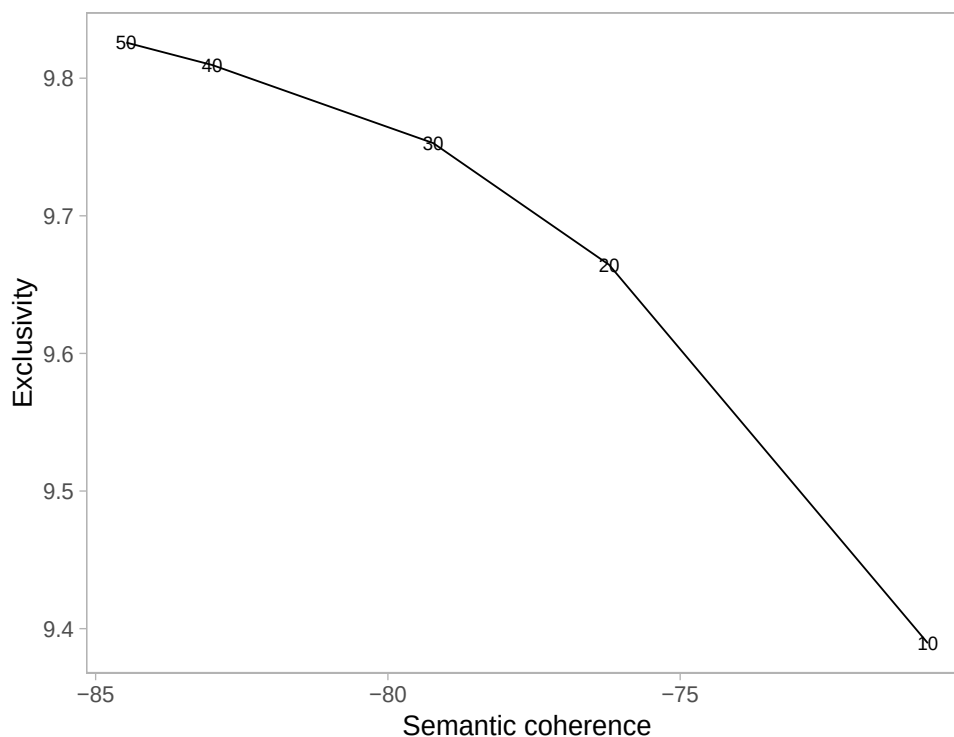


Appendix I. Topics analysis and media sources

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 I.8 shows the trade-off between semantic coherence and exclusivity across different topic numbers.

Figure I.8: 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 I.9 displays the correlation network of the 30 human capital topics.

Figure I.9: 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”).

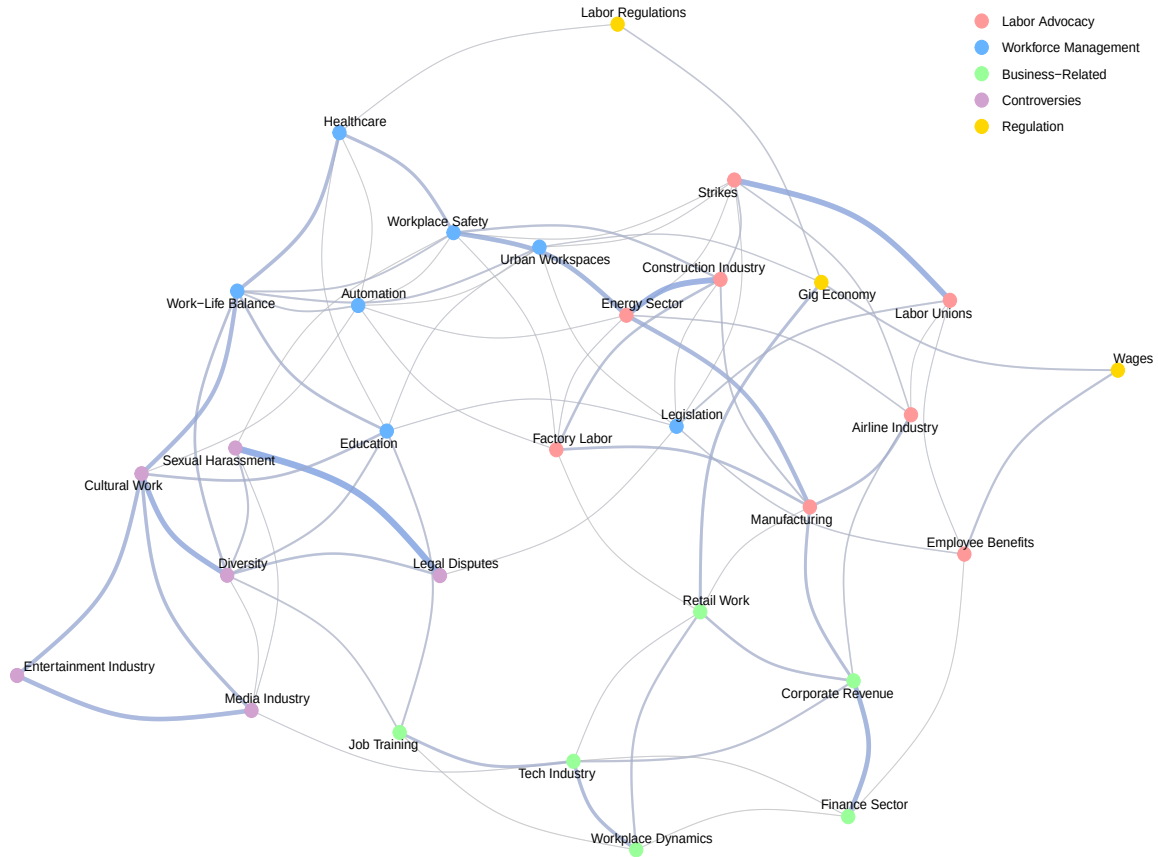


Table I.18 reports the labeled topics together with their ten highest-probability keywords. In Table I.19, we present the unconditional prevalence of topics and themes, along with their average concern scores. The unconditional prevalence of a topic is calculated as the average prevalence of the topic 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 I.18: 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 I.19: Topics' prevalence and concern score

This table reports the 30 topics' unconditional prevalence and average concerns 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 concerns 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,¹⁴ 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 I.20 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.

¹⁴The New York Times is a left-leaning newspaper, while the Wall Street Journal is right-leaning.

Table I.20: 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 concerns given different sources of newspapers. Columns 1 and 2 report the results using NYT source-specific index. Columns 3 and 4 report the results using WSJ source-specific index. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	<i>Dependent variable: Net flow (%)</i>			
	NYT (1)	NYT (2)	WSJ (3)	WSJ (4)
$HCC_{t-1} \times \text{Return}_{t-1}$	0.033** (0.014)		-0.001 (0.015)	
$HCC_{t-1} \times \text{Star}_{t-1}$	0.117*** (0.013)		0.089*** (0.013)	
$HCC_{t-1} \times \text{Env}_{t-1}$	0.017 (0.019)		-0.015 (0.018)	
$HCC_{t-1} \times \text{Soc}_{t-1}$	0.049*** (0.019)		0.024 (0.017)	
$\text{Index Business Related}_{t-1} \times \text{Return}_{t-1}$		0.041* (0.021)		0.049** (0.023)
$\text{Index Business Related}_{t-1} \times \text{Star}_{t-1}$		0.053*** (0.019)		-0.015 (0.020)
$\text{Index Business Related}_{t-1} \times \text{Env}_{t-1}$		0.044* (0.026)		0.017 (0.027)
$\text{Index Business Related}_{t-1} \times \text{Soc}_{t-1}$		0.023 (0.026)		-0.007 (0.027)
$\text{Index Labor Advocacy}_{t-1} \times \text{Return}_{t-1}$		0.039* (0.022)		-0.112*** (0.022)
$\text{Index Labor Advocacy}_{t-1} \times \text{Star}_{t-1}$		-0.032 (0.019)		-0.041** (0.019)
$\text{Index Labor Advocacy}_{t-1} \times \text{Env}_{t-1}$		-0.042 (0.026)		0.014 (0.028)
$\text{Index Labor Advocacy}_{t-1} \times \text{Soc}_{t-1}$		-0.044* (0.026)		-0.069** (0.028)
$\text{Index Controversies}_{t-1} \times \text{Return}_{t-1}$		0.010 (0.022)		-0.008 (0.019)
$\text{Index Controversies}_{t-1} \times \text{Star}_{t-1}$		0.019 (0.020)		0.011 (0.016)
$\text{Index Controversies}_{t-1} \times \text{Env}_{t-1}$		-0.022 (0.034)		-0.029 (0.023)
$\text{Index Controversies}_{t-1} \times \text{Soc}_{t-1}$		-0.036 (0.033)		0.003 (0.023)
$\text{Index Regulation}_{t-1} \times \text{Return}_{t-1}$		0.075*** (0.019)		0.086*** (0.018)
$\text{Index Regulation}_{t-1} \times \text{Star}_{t-1}$		-0.035** (0.017)		-0.026* (0.015)
$\text{Index Regulation}_{t-1} \times \text{Env}_{t-1}$		-0.009 (0.022)		-0.030 (0.019)
$\text{Index Regulation}_{t-1} \times \text{Soc}_{t-1}$		0.004 (0.021)		-0.009 (0.019)
$\text{Index Workforce Management}_{t-1} \times \text{Return}_{t-1}$		-0.078*** (0.026)		0.024 (0.022)
$\text{Index Workforce Management}_{t-1} \times \text{Star}_{t-1}$		0.115*** (0.022)		0.154*** (0.020)
$\text{Index Workforce Management}_{t-1} \times \text{Env}_{t-1}$		0.035 (0.036)		-0.014 (0.029)
$\text{Index Workforce Management}_{t-1} \times \text{Soc}_{t-1}$		0.120*** (0.035)		0.108*** (0.029)
Observations	263,519	263,519	263,519	263,519
Controls	Yes	Yes	Yes	Yes
COVID	Yes	Yes	Yes	Yes
Style $\times$ 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. Con-

sistent 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 concerns, 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 I.21 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 concerns on workforce management that drives the significance of the findings when the indices are aggregated.

Table I.21: 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 $\text{Source}_{\text{WSJ}}$ 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