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Comment les tendances des scores ESG façonnent l'attention et le sentiment des investisseurs

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Résumé

À mesure que l'investissement ESG gagne en importance, la relation entre les changements (tendances) des scores ESG et l'attention et le sentiment des investisseurs reste peu étudiée.

Cette étude analyse empiriquement la relation entre les variations des scores ESG et l'attention et le sentiment des investisseurs. L'analyse de sentiment est réalisée à l'aide du modèle Fin-BERT pour extraire des scores de sentiment à partir d'un ensemble de données d'articles financiers. L'étude utilise également des techniques de traitement automatique du langage naturel (NLP) pour compter le nombre de mentions des noms d'actions dans les articles de presse. Par ailleurs, d'autres proxys tels que les données de Google Trends, les logs d'EDGAR, le volume annuel des transactions, le nombre annuel de transactions et les mentions sur Twitter obtenues via Bloomberg sont utilisés pour mesurer l'attention des investisseurs, reflétant l'intérêt porté aux actions du S&P 500. Le sentiment des articles, basé sur Bloomberg, est également pris en compte, en complément des scores dérivés via Fin-BERT sur un échantillon d'articles financiers. La même méthodologie est appliquée au niveau sectoriel pour évaluer l'effet des scores ESG sur les secteurs, par opposition aux actions individuelles.

Les résultats indiquent une relation négative entre les variations des scores ESG et l'attention des investisseurs, cet effet étant plus prononcé au niveau des actions. En revanche, aucune relation significative n'a été observée entre les variations des scores ESG et le sentiment des investisseurs, que ce soit au niveau des actions ou des secteurs.

Mots clés : ESG, Investissement durable, Tendance des scores ESG, Attention aux actions, Attention médiatique, Traitement automatique du langage naturel (NLP), Grands modèles de langage (LLMs), Analyse du sentiment des actions

Abstract

As ESG investing gains prominence, the relationship between changes (trends) in ESG scores and investors' sentiment and attention remains underexplored.

This study empirically analyzes the relationship between changes in ESG scores and investor sentiment and attention. Sentiment analysis is conducted using the Fin-BERT model to derive sentiment scores from a dataset of financial news articles. The analysis also involves natural language processing (NLP) techniques to count the number of mentions of stock names in news articles. Additionally, other proxies include Google Trends data, EDGAR Logs, annual volume turnover, annual number of trades, and Twitter Publication Count from Bloomberg, which are utilized to capture investor attention and reflect search interest in stocks of the S&P 500. News head sentiment from Bloomberg is also used alongside the score derived using Fin-BERT on the sample of news articles to assess stocks' sentiment. The same methodology is used on the sector level to evaluate the effect of ESG scores on sectors instead of individual stocks.

The results indicate a negative relationship between changes in ESG scores and investors' attention, with this effect being more pronounced at the stock level. Conversely, no significant relationship was observed between changes in ESG scores and investors' sentiment, either at the stock level or the sector level.

Keywords: ESG, Sustainable investing, ESG score trend, Stock attention, Media attention, Natural Language Processing, Large language models, Stock Sentiment analysis

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List of Abbreviations and Acronyms

Abbreviation	Meaning
ESG	Environmental, Social, and Governance
EDGAR	Electronic Data Gathering, Analysis, and Retrieval
NLP	Natural Language Processing
SVI	Search Volume Index
SEC	Securities and Exchange Commission
ROA	Return on Assets
ROE	Return on Equity
CSR	Corporate Social Responsibility
MAE	Mean Absolute Error
LLM	Large Language Model
MSCI	Morgan Stanley Capital International
MDAX	Mid-Cap DAX Index
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
CSP	Corporate Social Performance
TSR	Total Shareholder Return

Table 1) This table provides a list of abbreviations and acronyms and their meanings which are frequently used in this study

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This work would not have been possible without their support and contributions, for which I am profoundly grateful.

Artificial Intelligence Utilization Disclosure

I declare that I have reached an agreement with my supervising professor regarding the use of generative artificial intelligence (AI) in the production of this thesis. I have utilized AI to assist in:

- **Citation Management and Formatting:** Utilized Mendeley for reference management and ChatGPT for assistance in formatting citations according to the required academic style.
- **Assistance in Literature Review:** Employed AI tools to assist in identifying the relevant literature to the research question.
- **Code Generation for Data Analysis:** Leveraged AI-assisted coding tools including Github copilot and ChatGPT to develop scripts for data analysis.
- **Editorial Refinement and Structural Improvements:** AI-assisted tools such as ChatGPT and DeepSeek were used to enhance sentence structure, improve clarity, and refine the overall coherence of the thesis.
- **Thesis Structure Optimization:** ChatGPT and DeepSeek were used to identify potential inconsistencies and improve the logical flow and coherence of the thesis structure.
- **Data Analysis and Data Entry:** AI assistance from ChatGPT was used to help organize datasets, perform preliminary data analysis, and guide data cleaning procedures.
- **Identification of Key Metrics and Proxies:** ChatGPT and DeepSeek were consulted to explore widely accepted financial metrics and attention/sentiment proxies referenced in the finance literature.
- **Table Formatting and Data Updates:** ChatGPT was used to assist in reviewing table formats and ensuring accuracy and completeness of dataset updates.
- **Chart Re-Creation:** Leveraged AI-powered design tools (Web plot digitizer) to regenerate charts with uniform formatting and color schemes, ensuring visual consistency and clarity across all thesis visualizations.

1 Introduction

Over recent years, Environmental, Social, and Governance (ESG) scores have become vital indicators for assessing companies' impact on both the environment and society. These scores, spanning Environmental, Social, and Governance dimensions, evaluate aspects such as ecological footprint, resource utilization, stakeholder relationships, labor practices, and corporate transparency. Initially tailored for financial institutions, ESG scores have gained widespread adoption due to their role in enhancing corporate image, reducing regulatory pressure, managing financial risks, and attracting investment. For investors, ESG scores function as tools for identifying and mitigating risks associated with environmental or social controversies that could negatively affect their portfolios (Clément, Robinot, & Trespeuch, 2023). While these metrics are effective in highlighting risks related to harmful practices or incidents, they face limitations in capturing the positive contributions companies make toward societal and environmental well-being. Efforts to promote sustainable behavior, particularly among smaller enterprises, continue to encounter challenges in accurately measuring their impact. Nonetheless, ESG scores represent a significant step forward in aligning financial investments with the United Nations Sustainable Development Goals, underscoring a broader commitment to responsible and sustainable business practices. Many professional money managers are starting to do in-house research about ESG scores and they have stopped relying solely on the ESG scores provided by other institutions. Figure 1 shows how ESG research has become entangled with investing firms.

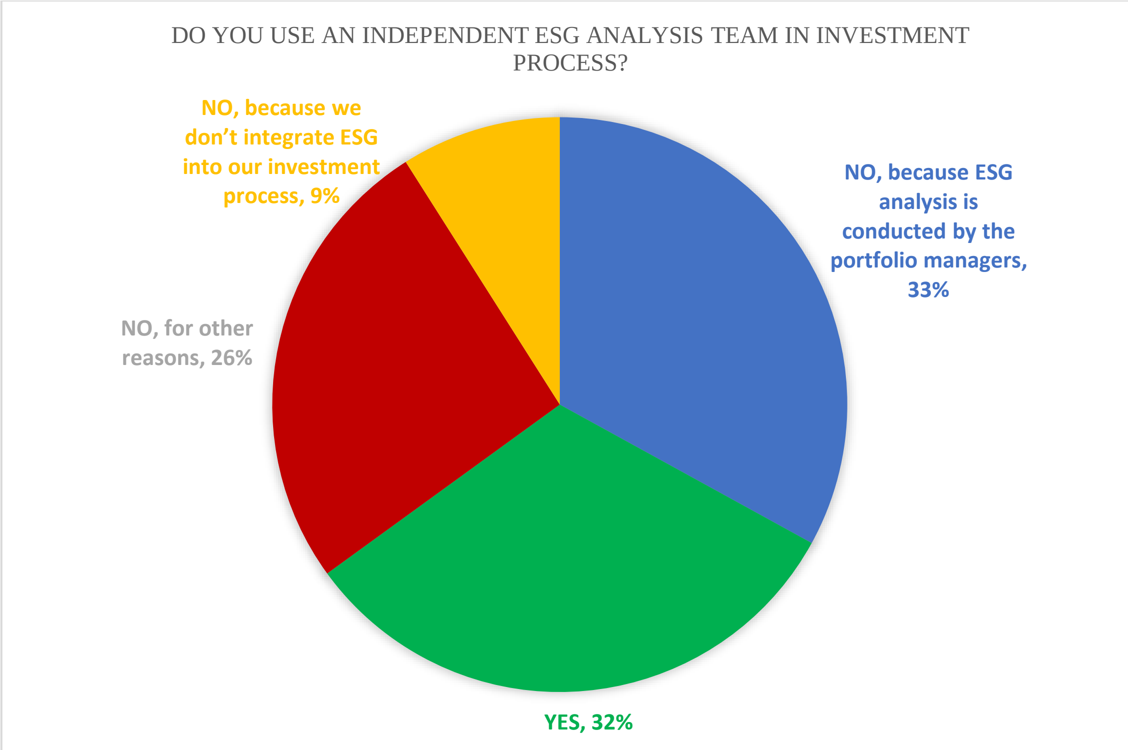

Figure 1) This chart illustrates the distribution of investment firms based on whether they use an independent ESG analysis team. The chart is a re-creation based on data from the CFA Institute ESG Report (2023).

According to Figure 1, some firms, especially smaller ones, may not have ESG specialists due to budget constraints or the nature of their investment strategies. Some firms choose to outsource ESG analysis rather than build in-house capabilities, while others do not see ESG as a priority or necessity. These differences reflect the broader debate in the investment industry about whether ESG should be a core responsibility of portfolio managers or a specialized function requiring dedicated experts. However, despite these structural differences, we can observe that a majority of investment firms, either directly or indirectly, include ESG in their investment process. Whether through dedicated teams, portfolio managers, or outsourced ESG analysis, ESG considerations remain relevant for a significant portion of investment organizations. This suggests that ESG is increasingly recognized as an important factor in investment decision-making, even if the level of integration varies across firms.

It is becoming increasingly difficult to ignore the impact of ESG scores in the world of investing. ESG investing is rapidly growing as more investors are interested in

Green Investing. Environmental, social, and governance (ESG) was first mentioned in a 2004 report endorsed by 18 financial institutions from nine countries and overseen by the United Nations Global Compact. Global sustainable investments reached over 35 trillion dollars in 2020, up from 30.6 trillion dollars in 2018 and 22.8 trillion dollars in 2016, and environmental, social, and governance assets are expected to exceed 50 trillion dollars by 2025, representing more than a third of the projected 140.5 trillion dollars in global assets under management (Global Sustainable Development Report, United Nations, 2023). This shows that investors are showing concern about investments that could have a negative effect on the environment and they are willing to drop off some of their options from their menu, to have a sustainable investment. Investors' willingness to forgo a portion of returns to align their investments with personal values is illustrated in Figure 2, highlighting the emphasis on value-driven investment decisions.

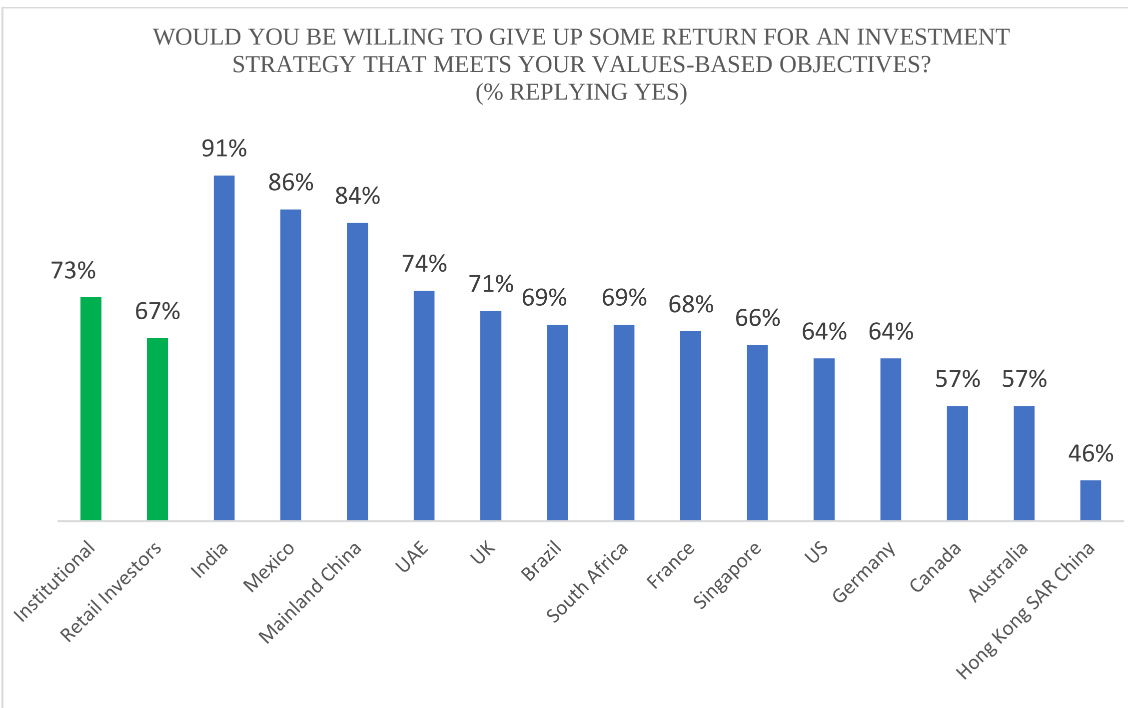

Figure 2) This chart presents the percentage of investors, both institutional and retail, who are willing to give up some financial return to meet values-based objectives. It also compares responses across different countries, highlighting variations in investor attitudes toward values-driven investment.The chart is a re-creation based on data from the CFA Institute ESG Report (2023).

As shown in Figure 2, both institutional (73%) and retail (67%) investors demonstrate a strong willingness to sacrifice financial returns to align with their values.

This indicates that ESG considerations have transitioned from a niche preference to a mainstream investment factor.

Figure 2 also reveals geographical differences, with investors in India showing the highest willingness, while Hong Kong SAR China has the lowest percentage. However, despite these regional differences, a significant portion of investors across all countries surveyed are willing to incorporate ESG principles into their investment approach. These findings reinforce the broader trend that ESG investing is gaining importance globally. While local investment cultures and regulatory environments may influence the degree of commitment, the overall data suggests that ESG is becoming a fundamental factor in investment strategies across institutional and retail segments, regardless of region. Figure 3 illustrates the rise in retail investor interest in ESG investing by country.

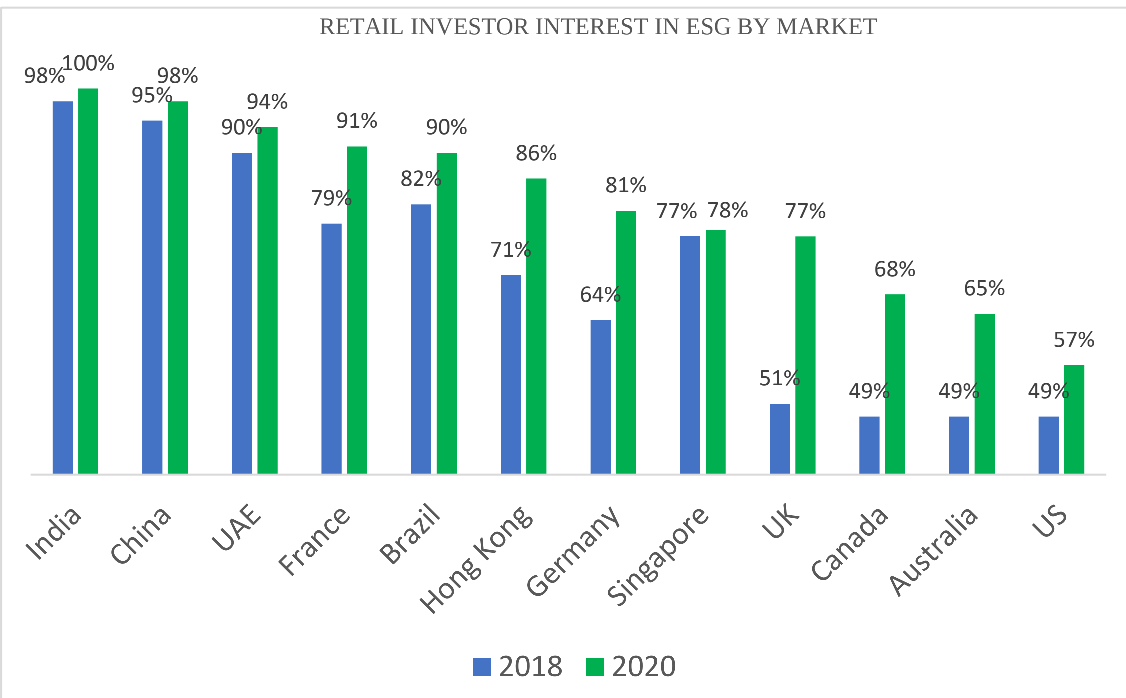

Figure 3) This chart compares the interest of retail investors in the year 2018 and 2020 sorted by different countries. The chart is a re-creation based on data from the CFA Institute ESG Report (2023).

Figure 3 depicts a consistent rise in retail investor interest in ESG across all markets from 2018 to 2020. While some countries already had high levels of interest and saw steady growth, others experienced a more rapid surge, reflecting a rising awareness of ESG investing. Markets with lower initial interest also showed notable improvements, indicating a broad global shift toward integrating sustainability into investment decisions.

This trend underscores the growing importance of ESG considerations among retail investors worldwide.

The increasing importance of Environmental, Social, and Governance (ESG) factors is reflected in initiatives like the Corporate Sustainability Reporting Directive (CSRD) and the SEC's proposed climate-related disclosure rule. These frameworks require companies to integrate sustainability data into their financial reports, highlighting the increasing demand for accurate, auditable, and timely sustainability data that meets the rigorous standards of traditional financial reporting (Pransky, Wilson, & Knickle, 2023). Figure 4 shows the relative interest of Google searches based on Google Trends. An increasing interest in ESG investing and ESG topics can be seen mostly stemming from the increase of interest in the Environmental pillar.

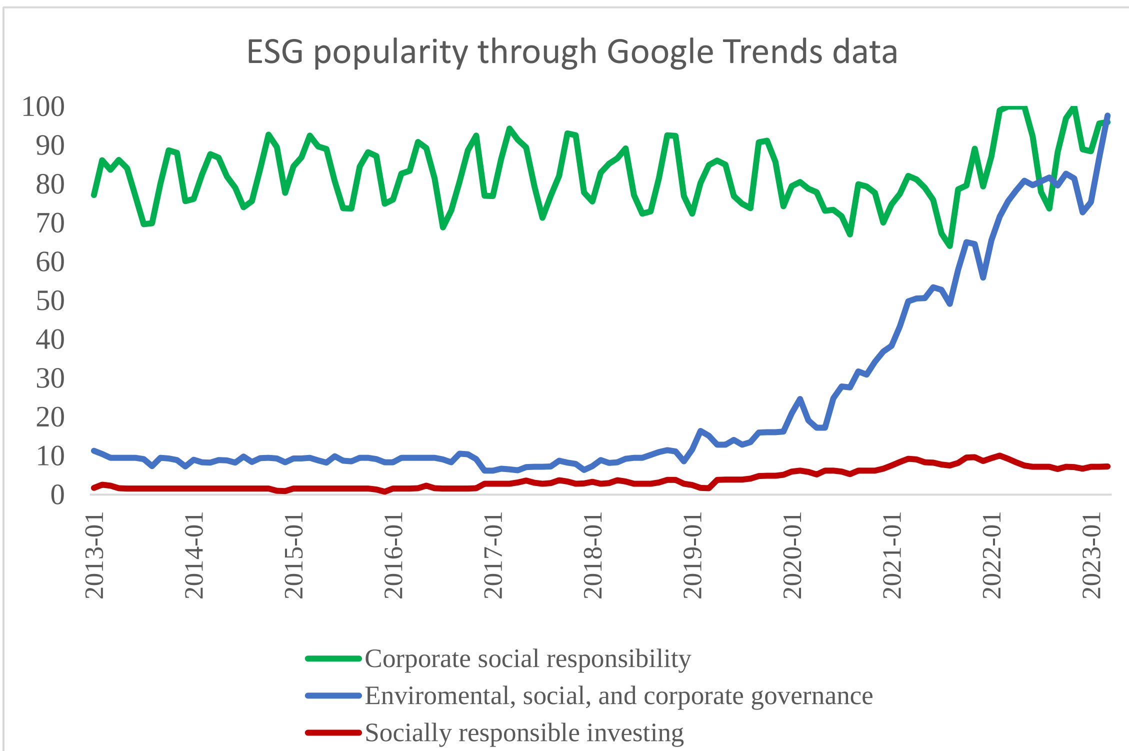

Figure 4) This graph shows the historical trends in global searches for topics like "environmental, social, and corporate governance," "corporate social responsibility," and "socially responsible investing" from January 2013 to January 2023. Chart re-created from Sustainable Finance and ESG Issues—Value versus Values article (Starks, 2023).

Figure 4 shows that interest in the *E* pillar is the main propellant of increase in the ESG interests. As more attention is absorbed toward the environmental pillar, studying ESG scores and their effects on investments is becoming increasingly important.

There have been various studies about the different impacts of ESG scores on stocks; Studied impacts include returns, different risk aspects, corporate-level aspects of a stock, and many other metrics that could add value to the asset management industry or regulators. For example, research by Samuel M. Hartzmark et al. (2019) provides a detailed analysis of investor responses to sustainability ratings introduced by Morningstar, which impacted over $8 trillion in mutual fund assets. Their research shows a significant and selective shift in fund flows based on these ratings. Specifically, funds awarded a high sustainability rating attracted over 24 billion dollars in net inflows, while those rated as having low sustainability saw more than 12 billion dollars in net outflows.

The launch of Morningstar's sustainability ratings was a pivotal moment in financial markets. Morningstar began classifying over 20,000 mutual funds based on their ESG practices. Funds with high ESG scores (top 10%) experienced significant inflows, whereas those with low ESG scores (bottom 10%) experienced substantial outflows. The remaining 80% of funds experienced no material change. This movement of funds highlights the strong market preference for assets perceived as sustainable. Their analysis also revealed that the introduction of sustainability ratings did not just alter fund flows; it also influences investor perceptions and expectations regarding the future performance of these funds (Hartzmark & Sussman, 2019). However, a notable research gap in the ESG literature is the absence of studies examining the impact of ESG score changes (trends) rather than the absolute levels of ESG scores. Understanding whether trends in ESG scores—whether positive (improving) or negative (declining)—affect investor attention and sentiment is crucial. This gap might be because the data history of the ESG score of companies was limited, as the ESG concept was introduced only in 2004, and many dominant data providers started providing ESG data more systematically after 2010 and major data providers included this data in their database only after 2018 however this limitation is being solved as now longer historical data of ESG scores are now available (CFA Institute, 2020).

Many companies have taken advantage of this trend and are using “Greenwashing” techniques to attract more attention to their stocks with the goal of lowering their cost of capital. (Yu, Luu, & Chen, 2020). It remains unclear whether improvements in ESG scores genuinely influence investor attitudes toward a company's stock.

This research aims to address the identified gap through two key research questions:

1) Is there a relationship between changes in ESG score and investors' level of Attention to a stock?
2) Is there a relationship between changes in the ESG score of a stock and investors' sentiment regarding that stock?

It is important to note that, given the myriad factors influencing investor sentiment and attention, this study does not aim to demonstrate a direct causal relationship between change of ESG scores and investor behavior. Instead, the primary focus is on establishing a simple relationship between these variables.

This analysis will enable company directors to make more informed decisions regarding the potential benefits of investing in ESG improvements. Specifically, it raises several critical questions: if a company invests in enhancing its ESG score, what benefits might accrue? Are investors more attentive to stocks with improving ESG scores? Furthermore, how do these improvements affect investor perceptions and sentiment towards the company?

This is important because, as ESG considerations become increasingly embedded in investment strategies and corporate governance, understanding their impact on investor behavior is critical. Identifying how changes in ESG scores influence attention and sentiment can provide companies with actionable insights to better align their sustainability initiatives with investor expectations. Moreover, as stakeholders demand greater transparency and accountability, this research helps bridge the gap between ESG performance and market perceptions, ultimately guiding corporate strategies toward fostering trust and achieving long-term value creation.

This paper is organized as follows. Section 2 reviews the existing literature on ESG investing and its relationships with various stock metrics. Section 3 describes the data and their sources. Section 4 outlines the methodologies employed for sentiment analysis and regression models. Section 5 presents the regression results and discusses findings, and Section 6 concludes the study. Section 4 presents the methodologies used to do sentiment analysis and regression equations. Section 5 presents the result of regressions and the discussion and section 6 concludes the results of the study.

2 Literature Review

As investors increasingly consider ESG scores in their investment decisions, research has broadened to examine the various dimensions and impacts of these scores within the financial sector. The literature can be broadly categorized into several themes. One theme investigates the relationship between a company's ESG score and its stock returns. Although this work falls under the asset pricing literature, it merits separate discussion due to its volume. Most studies in this area focus on ex-post returns without developing predictive trading strategies, and recent findings have even challenged the conventional wisdom regarding ESG.

Another theme explores the association between ESG scores and other stock characteristics, such as liquidity, credit ratings, and volatility. A further body of work examines ESG from a corporate finance perspective by investigating its relationship with financial ratios like ROA and ROE, as well as corporate indicators including employee wages and survival rates.

While most research emphasizes the absolute levels of ESG scores, there is limited work on how changes in these scores affect investor sentiment and attention. To address this gap, this review also considers studies that incorporate investor attention—detailing the proxies and methodologies used for its quantification. Additionally, relevant literature employs quantified measures of investor sentiment through sentiment analysis techniques, particularly those leveraging Natural Language Processing (NLP) methods and some pre-trained libraries like Fin-BERT and, more recently, Large Language Models (LLMs) such as ChatGPT.

2.1) ESG Scores and Financial Performance

Much of the ESG literature focuses on U.S. stocks, yielding conflicting evidence on the relationship between ESG scores and financial performance. Some studies find no clear link, while others report a positive association—and a few even indicate that higher ESG scores may increase operating costs and lower performance. Discrepancies largely arise from differences in data sets, stock selections, and time horizons. For example, Sharfman and Fernando (2008) investigate 267 S&P 500 firms and find that effective environmental risk management is associated with a lower cost of capital through reduced equity costs, a shift toward debt financing, and enhanced tax benefits. Similarly, Bruna et al. (2022) analyze 350 European listed companies (2014–2019) and conclude that ESG performance improves financial outcomes under stringent disclosure regimes.

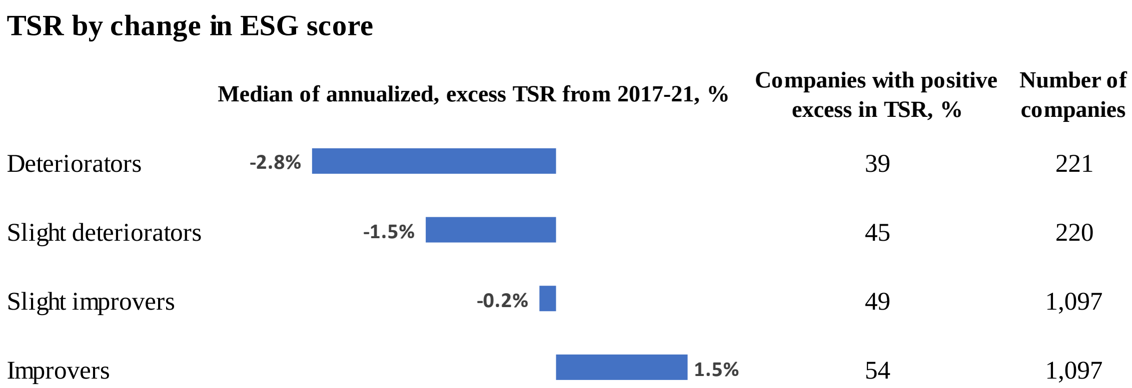

Figure 5) Annualized TSR is defined as the CAGR of the dividend-adjusted share price between 2017-2021 in companies' local currency. Data based on ESG scores of S&P Global for fiscal years 2017–2021. Chart recreated from "Does ESG really matter-and why?" McKinsey's article.

A few studies examine the evolution of ESG scores over time. McKinsey's analysis (Pérez, Hunt, Samandari, Nuttall, & Biniek, 2022 indicates that companies identified as ESG 'Improvers' tend to exhibit positive score trends and, on average, experience better total share returns, as illustrated in Figure 5. However, the influence of uncontrolled factors adds uncertainty to this relationship.

Recent literature also examines conditions under which 'green' stocks—companies with high environmental performance—may outperform 'brown' stocks, which have weaker environmental credentials. Pastor et al. (2020) demonstrate that green stocks tend to outperform the market in response to positive shocks, reflecting shifts in consumer and investor preferences toward sustainable investments. Ardia et al. (2021) further support this by employing a Media Climate Change Concerns index, showing that unexpected surges in climate-related worries drive superior returns for green firms. Later, Pastor et al. (2021) validate these findings by integrating the index into their equilibrium model.

Other studies find no conclusive evidence linking ESG scores directly to firm valuation. For instance, Aouadi & Marsat, (2018) examine over 4,000 firms across 58 countries (2002–2011) and find that while ESG controversies alone do not directly affect market value, their interaction with corporate social performance significantly enhances firm value—especially for high-visibility companies.

Lastly, a subset of the literature reports a negative relationship between ESG scores and financial performance. Duque-Grisales et al. (2021) analyze 104 'multilatina' companies from Brazil, Chile, Colombia, Mexico, and Peru (2011–2015), finding a negative correlation between higher ESG scores and financial returns, even after controlling for moderating factors such as financial slack and geographic diversification. They suggest that in emerging markets, institutional weaknesses, resource constraints, limited stakeholder recognition, and operational challenges may dilute the expected benefits of ESG integration.

2.2) ESG in Asset Pricing

Di Luo (2022) examines the relationship between ESG scores and stock liquidity in the UK using data from 2003 to 2020. His findings indicate that stocks with lower ESG scores tend to exhibit higher liquidity and, among less liquid stocks, returns are higher. This suggests that investors might perceive lower ESG-scored stocks as more attractive opportunities for short-term trading or speculative purposes. Using monthly value-weighted returns and ESG scores from Thomson Reuters, the study concludes that the ESG premium in stock returns is more pronounced for less liquid stocks.

Building on asset pricing research, several studies explore how ESG factors influence corporate risk assessments. For instance, Sang Kim et al. (2021) investigate the impact of ESG factors on corporate credit ratings and find that higher ESG scores are associated with better credit ratings. In a similar vein, they reveal that companies with robust ESG practices tend to have credit ratings that are, on average, one notch higher than those with weaker ESG practices. These results collectively underscore the growing recognition that effective ESG management contributes to financial stability and long-term sustainability.

In addition to traditional ESG scores, some research focuses on the disclosure of ESG information. Monica Singhania et al. (2024) develop a measure of firm-level ESG disclosure using Bloomberg ESG disclosure scores (ranging from 0.1 to 100). Their analysis demonstrates that increased transparency and more frequent ESG disclosures are linked to a reduction in idiosyncratic risk—risk that firms can manage directly—rather than systematic risk, which is driven by external factors.

Turning to market volatility, Abdessamad Ouchen (2022) compares the performance of ESG portfolios with market benchmark portfolios by applying Markov-switching GARCH models to data from the MSCI USA ESG Select and S&P 500 portfolios (June 2005 to December 2020). His results consistently show that ESG portfolios are less volatile than the broader market, suggesting that ESG considerations may offer a stabilizing effect.

Further extending the discussion to risk, Rio Murata et al. (2021) examine the relationship between ESG scores and stock price crash risk across different regions. Focusing on major indices such as the STOXX Euro 600, S&P 500, and Nikkei-225 and using Bloomberg data, they find that higher ESG scores are statistically associated with lower future crash risk in European and Japanese markets. However, in the U.S. market, this relationship does not reach statistical significance, highlighting regional differences in how ESG factors impact risk.

Finally, integrating the asset pricing perspective with portfolio performance, David Ardia et al. (2023) compare stocks with high ESG scores ("green stocks") to those with low ESG scores ("brown stocks") using S&P 500 data from 2014 to 2020. Their analysis reveals that approximately 20% of stocks distinguish themselves by generating positive alpha; however, this alpha advantage is declining over time—especially for green stocks. In contrast, variations in exposure heterogeneity appear more pronounced for brown stocks, suggesting that opportunities for differentiating factor exposures may differ by ESG performance.

2.3) ESG in Corporate Finance

Another strand of research examines ESG from a corporate finance perspective by exploring its impact on various accounting and operational metrics. For example, Patrick

Velte (2017) analyzes 412 firm-year observations from the DAX30, TecDAX, and MDAX indices (2010–2014) and finds that overall ESG performance positively affects ROA, indicating a significant link with improved accounting-based performance. In a related study, Alareeni and Hamdan (2020), citing Bassen and Kovács (2008), argue that ESG indicators capture aspects of firm performance—such as reputation, quality, brand equity, and safety—that traditional financial reports overlook; their work further demonstrates that a higher ESG index score is significantly and positively related to both ROA and ROE, with enhanced ESG disclosure improving operational and financial outcomes.

Extending the discussion to liquidity, Benjamin Liu et al. (2023) investigate the effect of ESG scores on cash holdings using 11,251 firm-year observations from US-listed companies (2006–2020). Their findings reveal that higher ESG scores are associated with lower cash holdings that lower the potential conflict of interest between shareholders and managers by limiting managers' ability to splurge corporate funds, suggesting better governance reduce the need for firms to maintain excess cash.

Research also focuses on the relationship between firm size and ESG scores. Samuel Drempetic et al. (2020) utilize data from over 6,000 companies (2004–2015) to show that larger firms tend to have higher ESG scores due to greater resources and more comprehensive ESG reporting; they caution that current measurement methodologies may be biased in favor of larger firms. In contrast, Sang Kim et al. (2021) find a generally positive correlation between ESG factors and corporate profitability, noting that larger firms derive greater benefit from sustainable practices. However, their findings do not specifically address potential biases in ESG rating methodologies.

Other studies within the corporate finance literature examine additional ESG dimensions, including the impact of ESG on employee retention (Liang et al., 2020), corporate portfolio composition, and increased institutional ownership in green firms (Sautner and Starks, 2019). These investigations offer a glimpse into the broad literature on ESG in corporate finance; however, further discussion of these topics is beyond the scope of the current research.

2.4) Investors' Attention

Investor attention is a prominent theme in the literature, with numerous studies examining its impact on stock returns and broader market dynamics. For example, Tao Chen (2017) investigates global stock returns using Google search volumes to quantify investor attention across 67 countries from January 2004 to December 2014, finding an inverse relationship between investor attention and subsequent stock index returns—a result that contradicts the investor recognition hypothesis which states higher investor attention is usually associated with lower required returns and thus higher prices. A similar inverse effect is demonstrated by Lily Fang and Joel Peress (2009), who, by analyzing media coverage of NYSE, S&P 500, and selected NASDAQ stocks from 1993 to 2002, observe that stocks with minimal media coverage earn higher returns than those with extensive coverage; this "no-media premium" is especially notable among small-cap stocks, those with high individual ownership, and stocks experiencing high idiosyncratic volatility.

Expanding on these findings, Zhi Da et al. (2011) use Google's Search Volume Index (SVI) for all stocks in the Russell 3000 (January 2004 to June 2008) and demonstrate that an increase in SVI predicts higher short-term stock prices over two weeks, followed by a reversal within the year—particularly in stocks heavily traded by retail investors. In a related vein, Kissan Joseph et al. (2011) employ online ticker searches as a proxy for investor sentiment for S&P 500 firms (2005–2008) and find that higher search intensity reliably predicts abnormal returns and increased trading volumes, especially for stocks with higher volatility.

Research distinguishing between retail and institutional investor attention further deepens our understanding of market behavior. Barber and Odean (2008) analyze comprehensive brokerage data from both individual and professional investors, revealing that individual investors are more inclined to buy stocks that attract attention through news coverage, high trading volumes, or extreme price movements—though such attention-driven purchases do not necessarily yield higher returns. Building on this, Nadia

Vozlyublennaia (2014) examines the influence of investor attention on various market indices (including the Dow Jones, NASDAQ, and S&P 500) using Google search query data; her results indicate that increased retail investor attention leads to short-term changes in index returns and affects return predictability differently across financial instruments or market segments, with larger stock indices and gold reacting more strongly than bonds or smaller stock indices.

Beyond return predictability, investor attention is linked to other market outcomes such as volatility. Ballinari, Audrino, and Sigrist (2020) differentiate between retail and institutional attention—measuring retail attention via social media activity (e.g., StockTwits) and institutional attention through Bloomberg terminal usage—and find that heightened retail attention around news releases increases post-announcement volatility, whereas greater institutional attention tends to mitigate it. In a broader market context, Tao Chen (2013) investigates herding behavior using daily returns from over 35,000 stocks across 69 countries (2000–2009) and uncovers significant evidence of herding, especially during market downturns.

Finally, integrating ESG considerations with investor attention, Meng et al. (2023) explore the mediating role of investor attention in the relationship between ESG performance and company reputation in the Chinese A-share market (2011–2021). Using the Hua Zheng ESG rating system and the Baidu Index to gauge attention, they find that higher ESG performance significantly enhances a company's reputation—particularly among non-state-owned firms.

2.5) Sentiment Analysis Using NLP

Another emerging strand of research applies Natural Language Processing (NLP) and sentiment analysis to financial markets, specifically stocks. Most scholars agree that advanced sentiment analysis methods—evolving from traditional bag-of-words approaches—can provide significant predictive power for market trends. A vast literature from computer science now employs NLP techniques to extract sentiment from textual data at both micro and macro levels.

For instance, Xiaodong Li et al. (2014) develop an innovative framework for stock price prediction by integrating six different NLP models. Their approach combines the Harvard Psychological Dictionary and the Loughran–McDonald financial sentiment dictionary to construct a sentiment space from five years of historical data on the Hong Kong Stock Exchange. Their results show that models incorporating sentiment analysis significantly outperform traditional bag-of-words methods, while simple sentiment polarity measures prove ineffective.

Building on this idea, Gupta and Chen (2020) demonstrate that financial sentiment extracted from StockTwits can enhance stock price movement predictions. Their method classifies tweets into positive and negative categories and reveals that the predictive power of aggregated daily sentiment declines gradually over multiple return lags. Their experiments on Apple, Amazon, General Electric, Microsoft, and Target confirm that integrating sentiment with past stock data improves forecasting accuracy.

Complementing these studies, Gilbert and Karahalios (2010) focus on the downside of market movements by developing an “Anxiety Index” from over 20 million LiveJournal posts. Their analysis, which does not filter by journal genre, finds that a one standard deviation increase in anxiety corresponds to a 0.4% decline in S&P 500 returns—illustrating the impact of heightened investor anxiety on market performance. Similarly, Pérez, Lucy, et al. (2016) use 2.5 million tweets to categorize sentiment into negative, neutral, and positive, and predict Microsoft’s stock direction for the following three days with over 70% accuracy. They note that recent advances like the Fin-BERT package reduce the need for extensive manual training data.

Several studies also combine sentiment analysis with ESG considerations. Serafeim (2020) examines how public sentiment influences market valuation for companies with strong ESG profiles. Using ESG scores from MSCI and sentiment data from TruValue Labs (collected from NGOs, media, and experts), his regression models show that positive sentiment momentum amplifies the valuation premium of high-ESG firms, while negative sentiment tends to weaken this premium, potentially signaling undervaluation risks rather than clear investment opportunities. In a similar vein, Rodrigo Zeidan (2022) analyzes over 13,000 ESG-related messages exchanged by finance professionals. His sentiment analysis reveals a predominantly skeptical tone among finance professionals, primarily highlighting significant concerns related to ESG data quality, transaction costs, and limitations imposed by strategy restrictions. Zeidan concludes that practical barriers to ESG investing extend beyond technical factors and require improved information quality and regulatory support to be overcome.

Recent advances in large language models (LLMs) further expand sentiment analysis capabilities. Fatouros et al. (2023) evaluate ChatGPT-3.5 for financial sentiment analysis in the foreign exchange market using a zero-shot prompting strategy. Analyzing forex news headlines over 86 days, they find that ChatGPT achieves approximately 35% higher sentiment classification accuracy and a 36% stronger correlation with market returns compared to the specialized Fin-BERT model. In contrast, Kocoń et al. (2023) assess ChatGPT across 25 NLP tasks—including sentiment analysis—and find that, although it performs well on tasks requiring nuanced understanding, it underperforms dedicated state-of-the-art models by about 25% on average.

Comparative studies also underscore the advantages of domain-specific models. Yang, Uy, and Huang (2020) demonstrate that their FinBERT model significantly outperforms the generic BERT model on financial sentiment classification tasks, achieving improvements ranging from 5.5% to 15.6% across multiple datasets. Extending this work, Zhuang Liu et al. (2021) train FinBERT on an extensive corpus exceeding 61 gigabytes of financial text, achieving a precision of 0.94 and an F1 score of 0.93 in financial sentiment analysis—thereby illustrating its capacity to interpret complex financial language effectively.

In conclusion, the literature reveals a chronological evolution in sentiment analysis. Early studies predominantly employ pre-trained NLP models (e.g., FinBERT), which mark a significant advancement in capturing financial sentiment from text. Recently, the emergence of large language models such as ChatGPT further transforms the field. While ChatGPT shows some improvements in accuracy and nuanced interpretation through zero-shot approaches, its performance is highly context-dependent. In the financial domain, ChatGPT may still underperform specialized models like FinBERT, and its limited explainability and inherent randomness in outputs pose substantial reproducibility challenges.

3 Data Gathering

For this study, the tickers of the S&P 500 index were utilized, encompassing all stocks that were added to or removed from the index during the six-year analysis period. In total, 564 stocks were included in the dataset, accounting for all additions and removals within the S&P 500 during the six-year period to ensure comprehensive coverage. For each stock, up to six years of ESG data were collected, though some stocks had incomplete ESG histories. This unavailability of data was not limited only to the ESG scores; Some proxies were also unavailable in some years; however, to keep as much as data possible for the study, even when there were missing data in the proxies the analysis was run on the remaining data. Since the analysis focused on annual differences rather than absolute ESG levels, a maximum of five annual data points were available per stock under optimal conditions. Stocks with fewer than five ESG data points were still retained in the study to preserve the robustness of the dataset. The inclusion of 564 stocks reflects the dynamic nature of the S&P 500, where companies are periodically added or removed, yet all were incorporated into the analysis to maintain consistency including the ones that were added to the index through the analysis period and were removed before the end of the analysis period. Stock tickers were obtained from Bloomberg Terminal data.

To establish clarity in the analysis, we begin by introducing the variable definitions in Table 2.

Variable	Definition
Google_Trend	A value between 0 to 100 showing the relative search interest of that word (stock name or ticker) in a specific year
ESG_SCORE	A value between 0 to 100 showing the ESG score of a company
ΔESG_SCORE	Difference of ESG score of a stock/sectore relative to last year
log_Mcap_begng_year	Natural logarithm of the market cap of the stock at the first trading day of the stock
Yearly_Return	Return of a stock in a specific year from the first day of trading until the last day included
Edgar	Number of web traffic logs generated from users accessing filings of stocks via the EDGAR system
Twitter_pub_cnt	Volume of tweets mentioning the entity's official ticker symbol, company name, or relevant keywords in a year
News_head_avg_sent	Average sentiment of news headlines or articles published about a particular stock over a year
average_weighted_sentiment	A number between -1 and +1, with +1 showing extreme positive and -1 showing extreme negative
repetition	Number of articles in the full name of a company was found in the 2000 news downloaded from NexisUni of a specific year

Table 2) Variable definitions table. This table presents the variables used in the analysis alongside their corresponding definitions.

ESG scores for each company, along with individual pillar scores, were collected from the Compustat database for the six-year period covering 2018 to 2023. Stock price data, used to calculate annual returns, was obtained directly from CRSP.

Market capitalization, which is later used to compute Log(Marketcap) for each stock, was determined by multiplying the stock price by the shares outstanding, both sourced from CRSP. In the regression equations, both *log_Mcap_begng_year* and *Yearly_Return* are incorporated as control variables to account for differences in firm size and performance.

Several proxies were utilized to measure investor attention to specific stocks, drawing from established methodologies in the literature. However, data for certain proxies, such as those from Robinhood, was unavailable. The proxies used in this study and their respective sources are outlined below:

1. “Number of Trades”, “Annual Share Volume” and “Annual Average Shares Outstanding” data was extracted from CRSP. The proxy of volume attention that was created for each stock was derived from dividing “Annual Share Volume’ by “Annual Average Shares Outstanding”.
2. "EDGAR Log", a proxy for measuring investor attention to a specific ticker, was obtained from the SEC's official website (www.sec.gov). These data were available only for the three years of 2020, 2021, and 2022 and each value shows the number of times a report of a stock was accessed through the sec website.
3. “Twitter Publication Count” (*Twitter_pub_cnt*) was obtained from Bloomberg Terminal. For each stock, this value shows the number of times tweets were mentioning a specific stock in a year.
4. Data for the *Google Trend* score (Google_Trend) widely recognized as the most common proxy for capturing investors’ attention, is utilized in numerous studies, including Chen (2017), to quantify search interest and measure investor behavior effectively. This score was obtained via the “Pytrends” library. which is an unofficial API wrapper for Google Trends. The language of the search was set to “en-US” to count only English searches over the whole year and no geographic location was given meaning that all the searches around the world were included in the calculation. To capture Google searches more comprehensively, both the trading symbol and full name of the company were used, and their respective scores were summed. Google Trends scores typically range from 0 to 100 individually; however, summing the separate scores for ticker and company name can artificially produce scores greater than 100. In cases where the total score exceeded 100, the value was clipped and replaced by 100 to avoid the influence of outliers in the regression. This adjustment affected less than 3% of all tickers in the dataset.

To feed the NLP model that gauges investor sentiment and counts the frequency of stock-name mentions, 12,000 news articles were collected. Due to practical constraints, downloading and analyzing every news article for each year was not feasible. Instead, a random sample of approximately 2,000 unique news articles was selected annually to serve as a representative subset of the year's total news output. The first 1,000 articles correspond to the year's first six months, while the remaining 1,000 cover the second half. These articles were sourced from Nexis Uni. To obtain more relevant results, the news was filtered to include only English-language articles, geographically limited to North America, and categorized under "Business News".

Another variable that measures the sentiment of a stock is "News head average Sentiment" (News_head_avg_sent) which is the sentiment of news headlines or articles published about a particular company or its stock over a year. This data was obtained from Bloomberg Terminal.

Table 3 demonstrates the summary statistics of the key variables used in this study.

data	Max	75th Prc.	median	mean	25th Prc.	Min	STD
Twitter_pub_cnt	15,212	14	6	47.3	2	0	393.1
News Head Average Sentiment	1	0.2	0	0.06	0	-1	0.41
EDGAR Logs	32,100,528	122,472	73,080	140,677	44,078	0	870,911
Google_Trend	100.0	84.3	73.7	68.7	56.2	3.3	19.2
News Count	6,349	18	5	81.3	2	1	415.4
sentiment	1	0.998	0.55	0.48	0.02	-1	0.51
Volume / Outstanding shares	607.7	14.8	6.4	13.6	2.6	0.06	29.9
Log Number of Trades	9.2	15.0	15.6	15.5	16.2	19.6	1.2
ESG_SCORE	91	54	42	44.5	33	10	15.5

Table 3) This table shows the summary statistics of the variables used in the study.

Table 3 summarizes key variables across all available years, providing an overall view of their distribution. However, it does not capture year-to-year variations. To offer deeper insights, Figure 6, Figure 7, and Figure 8 present annual trends, highlighting fluctuations in investor attention and sentiment proxies, as well as the ESG scores over the years.

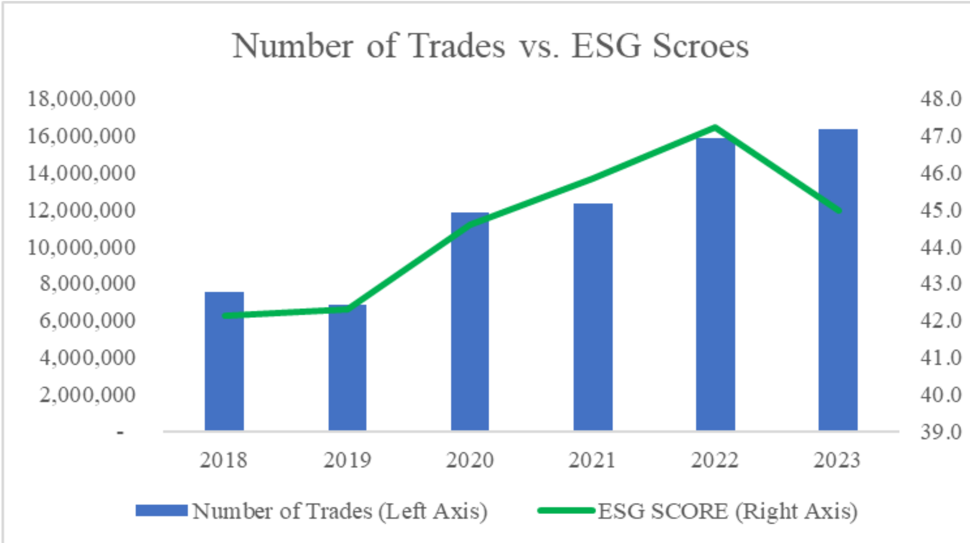

Figure 6) This figure shows the Number of Trades of all the stocks used in the analysis in a given year on the left axis and the average of their ESG score in that year on the right axis.

As shown in Figure 6, the number of trades has increased significantly over the analyzed period, largely driven by factors such as the wider adoption of high-frequency trading and reduced transaction costs. While the overall ESG scores of S&P 500 companies have also shown an upward trend, the rate of increase is considerably slower compared to the sharp rise in trading activity, which has more than doubled over this period. Additionally, the year 2020 exhibits a pronounced spike in trading volume, likely reflecting the heightened market volatility during the COVID-19 crisis. Similar anomalies can also be observed at the individual firm level. For instance, in 2023, the number of trades for Tesla, Inc. reached 341,009,837, more than 60 times higher than the median number of trades across all firms. To ensure that such outliers do not distort the regression results, a firm fixed effect are included in the model, as explained in more detail in the methodology section. This approach accounts for the fact that certain companies inherently attract a significantly higher volume of trades, preventing these firm-specific characteristics from biasing the analysis. To align with financial literature, the log transformation of trade counts was used in regressions to normalize their distribution and improve interpretability. This approach also mitigates the impact of extreme values, preventing extremely large trade volumes from disproportionately influencing results.

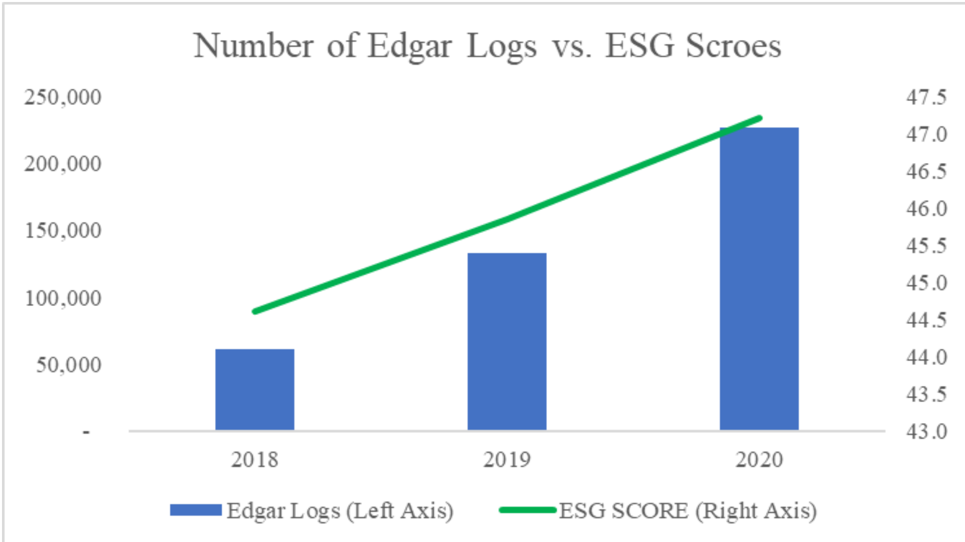

Figure 7) This figure shows the Number of EDGAR Logs of all the stocks used in the analysis in a given year on the left axis and the average of their ESG score in that year on the right axis.

A similar trend is observed in Figure 7, where EDGAR Log activity has also increased over time. This suggests a growing volume of regulatory filings and disclosures, potentially reflecting heightened investor interest in corporate disclosures and increased market volatility prompting more frequent document access. The data also reflects a notable jump in 2020, aligning with the market turbulence of that period. To account for annual temporal shocks and external factors affecting investor attention and sentiment, a time-fixed effect is incorporated into the regression equation, as detailed in the methodology section.

Regarding sentiment proxies, as previously explained, the first proxy, "average_weighted_sentiment," was derived from a dataset of 12,000 news articles, with the average sentiment for each year computed using the pre-trained FinBERT model. The second proxy, "News Head Average Sentiment" (*News_head_avg_sent*) was obtained directly from the Bloomberg Terminal. Figure 9 provides a comparative overview of these two sentiment proxies.

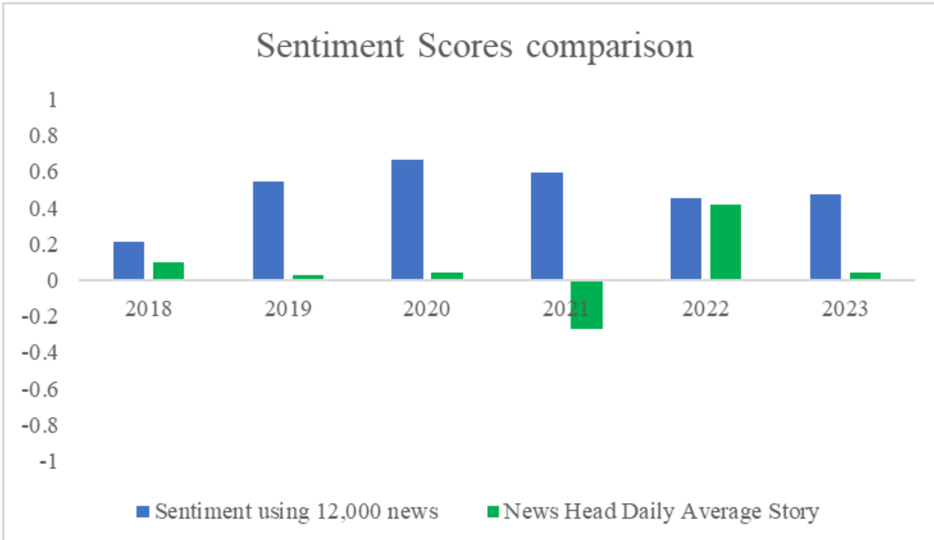

Figure 8) This Figure shows the average sentiment score of all the SP500 stocks in a given year.

As shown in Figure 8, the two sentiment proxies exhibit different results, with a correlation of -0.37. This divergence can be attributed to several factors. First, the input data differs between the two proxies; the *News_head_avg_sent* metric relies solely on news headlines, whereas the other sentiment proxy is based on a randomly selected sample of 12,000 full news articles. Additionally, the news used in each proxy may vary, contributing to the discrepancy. Second, differences between the pre-trained FinBERT model and Bloomberg's proprietary sentiment analysis approach could lead to substantial variations in sentiment scoring. Lastly, due to FinBERT's 512-token limit, sentiment analysis was restricted to the initial portions of longer articles, likely omitting relevant contextual and sentiment cues present deeper in the text. These methodological and data differences have collectively contributed to the observed divergence between the two proxies.

4 Methodology

As noted in the Literature Review section, although a range of LLM models is available for sentiment analysis, two models have emerged as the most widely utilized in the literature:

1) FinBert
2) ChatGPT

In this study, we chose FinBERT over ChatGPT for sentiment analysis of stock-related news due to its specific fine-tuning for financial sentiment analysis. FinBERT is designed to understand and classify financial text with higher accuracy, making it more reliable for analyzing market sentiment compared to the more general-purpose ChatGPT.

4.1 Associating News to Stocks

In total, 12,000 news articles were used and each news is associated with a stock. The association of news articles with stocks was conducted using the NER module of the spaCy Natural Language Processing (NLP) library. This process involved applying spaCy's pre-trained Named Entity Recognition (NER) model to identify organization names within the text of each article. The recognized entities were then matched against a list of company names. If a match between a recognized entity and a listed company was identified, the news article was linked to the corresponding stock ticker. This method allowed for the identification of company names even when variations, such as abbreviations or slight differences in phrasing, were present. Articles mentioning multiple recognized companies were associated with all corresponding stocks, whereas articles lacking any identified company names were excluded from the analysis. The use of NER module ensured that the analysis focused on news articles that could be accurately linked to specific stocks, enhancing the relevance of the results. For example, consider a news article that mentions "3M" in the context of discussing a new product launch or a financial update. The spaCy model, through its Named Entity Recognition (NER) module, identifies "3M" as an organization within the text. In addition to recognizing the full company name "3M Company," the model is also capable of detecting the abbreviation "3M" and even the ticker symbol "MMM" as referring to the same entity. This is particularly important in financial news where companies are often mentioned by their abbreviated names or ticker symbols. So, when "3M" or "MMM" is identified in the article, the model matches it to "3M Company" in the predefined list of company names. Using this methodology, some news articles were assigned to multiple stocks, while others were not assigned to any stock and, therefore, were excluded from the model. This occurred because, among the original 12,000 business news articles downloaded, some did not specifically reference any S&P 500 constituent.

It is worth noting that before this approach, a simple string parsing method was used and the text was searched for the exact match of the full name of the company (in small and capital letters); however, this method was not efficient because in some news only tickers of companies are used instead of the full names or sometimes a part of the full name is mentioned. For example, in this method in order to associate a text to “Facebook” the exact name of the company “Meta Platforms, Inc.” should be found exactly; In contrast, the NER module of spaCy is able to detect different similar names, including the company's ticker symbol 'META', and accurately associate the news article with the stock.

4.2 Calculating “Number of Media Mention Repetition”

Following the previous step, 2,000 news articles per year are associated with specific stocks. For each stock, the variable 'Repetition' is calculated by counting the number of news articles mentioning that stock within a given year. This variable serves as a proxy for investor attention in the regression models of Equation 2 and Equation 3. 'Repetition' quantifies the frequency with which a stock is referenced in the news, providing an indicator of the level of attention it receives from investors.

4.3 Assessing the Sentiment of News

FinBERT, a pre-trained large language model, was utilized to derive a numerical value for the sentiment of each stock. FinBERT provides three probabilities for each news article: the first probability represents the likelihood that the text conveys a positive sentiment, the second represents the probability of a neutral sentiment, and the third indicates the probability of a negative sentiment. To convert these results into a quantitative value, we assign a numerical value of 1 to positive news, -1 to negative news, and 0 to neutral news. Subsequently, an 'Average Sentiment Weight' score for each news article is computed by multiplying each sentiment category's numerical value by its respective probability, resulting in a weighted sentiment score. To formalize this computation, Equation (1) defines the calculation of the sentiment score (average_weighted_sentiment), incorporating both the sentiment probability derived from FinBERT and the assigned numerical sentiment value.

$$\text{Average weighted Sentiment} = \text{probability} * \text{numerical value of sentiment} \tag{1}$$

It is important to note that Fin-BERT has a limit of 512 tokens. If the input news text exceeds this limit, only the first 512 tokens are processed by the model. This token limit includes the headline of the news and the beginning part of the news, which typically contains the majority of the information relevant to the sentiment of the article.

4.4 Regression Equations

To analyze the relationship between ESG scores and investors' attention and sentiment, a panel regression model is employed, structured as panel data where the first index represents time (t) and the second index corresponds to individual stocks (i). The regression framework includes log(Mcap), the logarithm of market capitalization at the beginning of the year, and Yearly_return, the annual return of the stock, as control variables. stocks with larger market capitalizations, such as Apple or Google, tend to attract greater investor attention and media coverage, making it essential to account for their influence. Similarly, annual stock returns can independently affect investor attention, reflecting performance-related factors and broader market conditions. Controlling for these variables ensures that the estimated effect of change in ESG scores (ΔESG_SCORE) on investor attention and sentiment proxies is isolated, mitigating potential confounding effects.

The regression model used in this study is specified in Equation (2).

$$\text{Proxy}_{it} = \beta_0 + \beta_1.\ \Delta\text{ESG\_SCORE}_{it} + \beta_2.\log(\text{Mcap})_{it} + \beta_3.\text{Yearly\_return}_{it} + \varepsilon_{it} \qquad (2)$$

This specification allows for the estimation of the effect of ΔESG_SCORE on various investor attention and sentiment proxies while controlling for firm size and stock performance.

In the regression model, both time-fixed effects and firm-fixed effects were incorporated. Time-fixed effects were included to account for temporal variations in investor sentiment and attention across different years. For instance, during 2020, overall investor sentiment toward the stock market was lower compared to other years in the sample period. Controlling for these time-specific factors prevents confounding effects, isolating the relationship between changes in ESG scores (ΔESG_SCORE) and investor attention.

Firm fixed effects were included to address inherent differences across stocks. Stocks in different sectors attract varying levels of sentiment and attention due to their firm-specific and industry-specific characteristics; for example, the real estate sector inherently attracts higher investor sentiment (see Appendix A for sentiment comparison and Appendix B for sector media coverage (repetition)). By incorporating firm fixed effects, the model controls for these stock-level variations, ensuring that the analysis isolates the effect of ΔESG_SCORE from other persistent, unobservable factors unique to each stock.

In Equation 2 *proxy* is replaced by six different variables for measuring investors' attention:

1. ***Google Trend Score:*** Google Trends provides a score between 0 and 100 for each word, representing the relative search interest for that term over a specified period. A score near 100 indicates that the term (in this case, the stock) is being searched frequently by users. Due to this characteristic, the Google Trend score is often used in finance literature as a proxy for measuring investors' attention to a specific stock in the modern era in which investors use Google to search for news.

2. ***Annual Share Turnover (Volume / Outstanding Shares):*** Annual share turnover is calculated as the total trading volume of a stock over a year divided by its outstanding shares. This adjustment is necessary to make the trading volume of stocks comparable across companies with varying share counts. For instance, companies like Apple, with approximately 4 billion outstanding shares, naturally exhibit higher trading volumes compared to companies like AutoZone Inc., which has fewer than 20 million shares. By normalizing trading volume through division by outstanding shares, the resulting turnover values allow for meaningful comparisons. In financial literature, share turnover is widely recognized as a proxy for investor interest and trading behavior, as higher turnover typically indicates greater investor engagement and attention.
3. ***Log(Number of Trades)***: The sum of the *Number of Trades* throughout a year serves as an effective proxy for capturing the engagement of retail investors. This is because retail investors typically trade in smaller volumes compared to institutional investors. As a result, this measure provides a more accurate representation of retail investor activity compared to annual share turnover, which is more reflective of overall trading behavior. Since *Number of Trades* has a skewed distribution, and some firms have a very high number of annual trades. So a logarithmic transformation is applied to normalize the distribution and reduce the disproportionate influence of extreme values.
4. ***EDGAR Logs***: This variable measures the number of times filings for a specific company were accessed by users on the SEC website. A higher number of visits and downloads indicates increased interest, suggesting greater attention is being paid to the stock by investors or institutional analysts.
5. ***Twitter Publication Count:*** *Twitter_pub_cnt* variable, obtained from Bloomberg Terminal, represents the number of tweets or Twitter mentions related to a specific stock within a given period (in this study one year). This variable primarily captures retail investors' attention.
6. ***Number of Media Mention repetition (Among 12,000 News Articles):*** After associating each piece of news with relevant stocks, the number of news articles mentioning a particular stock was calculated annually. Since there are 2,000 news

articles per year in the dataset, each stock receives a value ranging from 0 to a maximum of 2,000, depending on the number of articles that reference it within that year.

finally, *the proxy* was replaced by the *sentiment score* of each stock to assess the effect of the ΔESG_SCORE on the sentiment of each stock. There are two variables that represent the sentiment of each stock during a year:

1. ***News Head Average Sentiment:*** The *News_head_avg_sent* variable was obtained from the Bloomberg Terminal. Its inclusion, compared to the sentiment derived from the analysis of 12,000 news articles, is motivated by Bloomberg's different media coverage, which encompasses a wider range of sources and perspectives.
2. ***Average_weighted_sentiment (12,000 News Articles):*** This variable represents the average sentiment score of news articles associated with a specific stock over a given year. The sentiment scores were calculated using the FinBERT model.

In contrast to the attention analysis, which reflects clear differences between small-cap and large-cap stocks, the sentiment analysis does not exhibit systematic variations in investor sentiment across these groups. For example, although the trading volume for a large-cap company like Tesla is substantially higher than that for a smaller firm, the sentiment scores are constrained within a range (between -1 and +1) regardless of market capitalization. Consequently, the control variable *log(Mcap)* was excluded from the regression in Equation 2 for sentiment proxies.

Equation 2 captures the contemporaneous relationship between ΔESG_SCORE and the proxies, examining their association within the same year. However, there is a potential for omitted variable bias in this Equation. This occurs when an unobserved variable (Z) simultaneously influences both the ΔESG_SCORE (X) and investor sentiment or attention (Y), leading the regression to produce spurious results. To address this issue, we modify the regression by replacing the current ΔESG_SCORE_t with its lagged value (ΔESG_SCORE_{t-1}).

The regression model incorporating the lagged ΔESG_SCORE is specified in Equation (3). In this formulation, ΔESG_SCORE is lagged by one year, meaning it reflects the difference in ESG scores between t-1 and t-2 for firm i, rather than the contemporaneous change. The control variables remain the same, with log(Mcap) representing the logarithm of market capitalization at the beginning of year t, and Yearly_return capturing the stock's return during year t.

The mathematical representation of this predictive regression model is illustrated in Equation 3.

$$\text{Proxy}_{it} = \beta_0 + \beta_1.\ \Delta\text{ESG\_SCORE}_{i(t-1)} + \beta_2.\log(\text{Mcap})_{it} + \beta_3.\text{Yearly\_return}_{it} + \varepsilon_{it} \qquad (3)$$

Equation 3 accounts for the possibility that the relationship between ΔESG_SCORE and investor attention or sentiment may not occur within the same year. For instance, an improvement in a company’s ESG score in one year could influence investor sentiment and attention in the following year. This aligns with the initial hypothesis that, in practice, if a company enhances its ESG performance, investors may subsequently pay more attention to the stock, and their sentiment toward it may improve over time.

Similar to the previous discussion, in sentiment analysis regressions, unlike attention analysis, there is no difference between investors’ sentiment regarding small cap stocks versus large cap stocks, the control variable *log(Mcap)* is removed from the regression of Equation 3.

Regressions in Equation 2 and Equation 3 can also be applied at the sector level instead of focusing on individual stocks within the S&P 500. Conducting the analysis at the sector level offers several advantages. First, stock-level data often exhibits high volatility due to company-specific factors such as management decisions, short-term events, or earnings surprises. Aggregating stocks into sectors helps smooth out these idiosyncratic variations, allowing for a clearer analysis. Additionally, this approach better accounts for unobserved factors that influence all stocks within a sector, such as industry-wide trends or macroeconomic conditions. Second, sector-level analysis aligns more closely with the decision-making processes of many institutional investors, who often base their strategies on sectors rather than individual stocks. For instance, some investors may choose to divest from the energy sector as a whole due to ESG concerns, reflecting the broader focus on sector-level characteristics.

To calculate the variables that will be put as the '*proxy*' in Equation 2 and Equation 3, an equal-weighted average of the stock-level scores was utilized. This method ensures that all stocks are represented equally, preventing the overrepresentation of stocks with larger market capitalizations. Therefore, the proxies, including the eight variables and also the ΔESG_SCORE for each sector, were computed by taking a simple average of their respective constituents. Overall, eight regressions were run based on Equation 2 and eight regressions based on Equation 3.

5 Discussion and Results

This section presents the panel regression results from Equation 2 and Equation 3. In these models, eight *proxies* are employed—two for investor sentiment and six for investor attention, as described previously—yielding a total of 16 regression outcomes.

In each regression, the number of observations varies because some proxies are unavailable for certain stocks in specific years. Since the analysis is conducted on panel data—covering different stocks over a five-year period—three different R^2 measures are reported. The first, R^2 within, measures how well the model explains variations within individual stocks over time. The second, R^2 between, assesses how well the model explains variations across different stocks, while the overall R^2 provides a general measure of fit that accounts for both within-stock and between-stock variations. Given that the primary research objective is to determine whether a relationship between change of ESG score and investors' sentiment and attention exists, the overall R^2 is considered the most relevant indicator.

The results are presented in four tables. Two tables provide stock-level analyses; the first presents the contemporaneous regression results (Equation 2), and the other examines the lagged change in the ESG score (ΔESG_SCORE_{t-1}) as outlined in Equation 3. Similarly, the remaining two tables offer sector-level analyses, with the first assessing the contemporaneous relationship and the second evaluating the lagged relationship. For the sector-level calculations, an equally weighted average was applied to the proxies, the ΔESG_SCORE, and all control variables rather than a market capitalization-weighted approach. This methodological choice was implemented to prevent the overrepresentation of large-cap stocks and the underrepresentation of small-cap stocks.

Table 4 and Table 5 show the results of contemporaneous panel regression on the stock level:

	Equation 2 Regression Result on Attention Proxies on the Stock Level					
	Google Trend	Volume / Outstanding shares	Log Number of Trades	Edgar Logs	Twitter Publication Count	Number of Media Mention (Repetition)
Intercept (β_0)	47.26***	73.609***	13.167***	-1039.6	242.29**	-9.7235
T-stat	3.4844	9.445	14.3310	(0.2576)	2.1209	(0.3863)
Proxy Coefficient (β_1)	0.017	-0.0078	-9.00E-04	2.7903	-0.4863**	-0.1517***
T-stat	0.7039	(0.5582)	-0.6663	0.4383	(2.3860)	(3.3359)
R-squared (Overall)	-0.0175	0.0583	0.0262	0.014	-0.0546	0.016
R-squared (Between)	-0.0209	0.0534	0.2259	0.0238	-0.0649	0.019
R-squared (Within)	0.0051	0.0529	0.0989	0.0024	0.0049	0.0122
No. Observations	2407	2400	698	1346	2368	1920
Included effects	Entity, Time	Entity, Time	Entity, Time	Entity, Time	Entity, Time	Entity, Time

* 10% Significance, **5% Significance, ***1% Significance

Table 4) This table presents the results of the coefficients from Equation 2 regression on the stock level for investor attention proxies. Each regression is conducted independently for a single proxy. All variables in this equation are contemporaneous, meaning they correspond to the same year (t).

	Equation 2 Regression Result on Sentiment Proxies on the Stock Level	
	News Head Daily Average	Media Sentiment (12,000 news articles)
Intercept (β_0)	0.0685***	0.5208***
T-stat	7.3227	31.666
Proxy Coefficient (β_1)	-0.00007251	-0.0023
T-stat	-0.0731	(1.1511)
R-squared (Overall)	-0.0065	-0.0067
R-squared (Between)	-0.006	-0.0114
R-squared (Within)	-0.007	0.0125
No. Observations	1877	728
Included effects	Entity, Time	Entity, Time
	* 10% Significance, **5% Significance, ***1% Significance	

Table 5) This table presents the results of the coefficients from Equation 2 regression on the stock level for investor sentiment proxies. Each regression is conducted independently for a single proxy. All variables in this equation are contemporaneous, meaning they correspond to the same year (t).

As illustrated in Table 4 and Table 5, ΔESG_SCORE exhibits a statistically significant negative effect only on two proxies: Twitter Publication Count (*Twitter_pub_cnt*) and Number of Media Mention (*Repetition*). However, their coefficient is negative meaning that firms experiencing a decrease in ESG scores tend to receive more attention. This negative relationship suggests that investors and media pay increased attention to companies whose ESG performance is deteriorating, possibly due to concerns over the negative implications of worsening sustainability practices. Conversely, improving ESG scores may attract less scrutiny or media coverage.

Among the sentiment proxies, none reject the null hypothesis ($\beta 1=0$), indicating that the regression, after controlling for market capitalization and yearly return, does not find a significant relationship between in a stock's ΔESG_SCORE and its sentiment. This indicates that variations in ESG scores do not exhibit a statistically significant relationship with sentiment proxies, thereby failing to reject the null hypothesis ($\beta_1=0$).

The overall R-squared values obtained from the regression analyses are notably low, and in some instances, even negative. This indicates that, although the regression models identify statistically significant relationships for certain proxies, their explanatory power remains limited. Consequently, the observed variations in investors' attention and sentiment are predominantly influenced by factors other than ΔESG_SCORE. This outcome is somewhat anticipated, suggesting that changes in ESG scores, while relevant, are not among the predominant factors that systematically drive investor attention or sentiment. Thus, while ΔESG_SCORE may contribute to explaining investor behavior to some extent, it does not serve as a primary or dominant driver of investors' attention and sentiment.

It can be concluded that ΔESG_SCORE influences investors' attention to a stock within the same year, albeit with a negative relationship. Specifically, improvements in ESG scores tend to correlate with reduced investor and media attention, while declines in ESG scores appear to trigger increased scrutiny and coverage.

Table 6 and Table 7 show the result of panel regression on the stock level but on the Lagged series of ΔESG_SCORE.

	Equation 3 Regression Result on Attention Proxies on the Stock Level					
	Google Trend	Volume / Outstanding shares	Log Number of Trades	Edgar Logs	Twitter Publication Count	Number of Media Mention (Repetition)
Intercept (β_0)	60.144**	75.134***	14.351***	-3059.8	306.93**	-0.0017
T-stat	3.2564	7.367	22.4340	(0.3159)	2.3319	(0.0383)
Proxy Coefficient (β_1)	-0.25	-0.0279*	0.17**	1.7946	0.0658	4.1263
T-stat	-0.8884	(1.7954)	2.2187	0.1639	0.2822	(0.1635)
R-squared (Overall)	-0.0059	0.0632	0.0719	0.0262	-0.0754	0.0044
R-squared (Between)	-0.0078	0.0569	0.165	0.0376	-0.0858	0.0074
R-squared (Within)	0.0044	0.0727	0.1159	0.0011	0.0055	0.0006
No. Observations	1903	1897	542	888	1877	1920
Included effects	Entity, Time	Entity, Time	Entity, Time	Entity, Time	Entity, Time	Entity, Time

* 10% Significance, **5% Significance, ***1% Significance

Table 6) This table presents the results of the coefficients from Equation 3 regression (lagged version of ΔESG_SCORE) on the stock level for investor attention proxies. Each regression is conducted independently for a single proxy. In this equation, the ΔESG_SCORE is lagged by one year, while all other variables remain contemporaneous, corresponding to the same year (t).

	Equation 3 Regression Result on Sentiment Proxies on the stock level	
	News Head Daily Average	Media Sentiment (12,000 news articles)
Intercept (β_0)	0.0716***	0.5209***
T-stat	7.4952	29.786
Proxy Coefficient (β_1)	-0.0015	0.0027
T-stat	-1.5147	1.2040
R-squared (Overall)	-0.0065	0.0025
R-squared (Between)	-0.006	-0.0042
R-squared (Within)	-0.007	0.0178
No. Observations	1877	586
Included effects	Entity, Time	Entity, Time
	* 10% Significance, **5% Significance, ***1% Significance	

Table 7) This table presents the results of the coefficients from Equation 3 regression (lagged version of ΔESG_SCORE) on the stock level for investor sentiment proxies. Each regression is conducted independently for a single proxy. In this equation, the ΔESG_SCORE is lagged by one year, while all other variables remain contemporaneous, corresponding to the same year (t).

According to the Table 6 and Table 7, when a one-year lag of ΔESG_SCORE is incorporated into the regression equation—thereby assessing the impact of lagged ΔESG_SCORE on investor attention and sentiment—The sentiment proxies again fail to reject the null hypothesis (β_1=0), indicating no statistically significant relationship between lagged ΔESG_SCORE and investor sentiment. Therefore, same as contemporaneous results, sentiment of stocks remains unchanged even after one year lag.

Among the attention proxies, the *Log Number of Trades* is positive and statistically significant at the 5% level, indicating a positive association with lagged ΔESG_SCORE. This suggests that trading activity increases for stocks with improving ESG scores, even with a one-year delay. Conversely, Volume/Outstanding Shares is marginally significant with a negative coefficient, showing a weak negative relationship with lagged ESG score changes, suggesting that lower ESG scores still attract investor attention in some capacity.

In this model which examines the lagged relationship of ΔESG_SCORE and investors' attention proxies, in contrast to the contemporaneous model, the significance of two *Twitter_pub_cnt* and *Repetition* proxies is lost. These two proxies mostly represent the attention of the media. However, the other two proxies that are significant in the lagged model, *Volume / Outstanding shares* and *Log Number of Trades* predominantly capture the investors' attention through trading activity. This difference potentially shows that changes in the ESG scores are captured and boldened by the media immediately in the same year but Investors increase their trading activity in the following year with a time lag.

Another interesting finding is that the coefficient of the ΔESG_SCORE (β_1) is positive for *Log Number of Trades* and negative for *Volume / Outstanding shares*. Since *Log Number of Trades* typically reflects activity among individual or smaller investors, while *Volume / Outstanding Shares* primarily captures institutional or larger investors, this difference in the signs of β_1 might suggest that ESG score changes are associated differently with the trading behaviors of smaller versus larger investors.

The overall reduction in statistical significance compared to the contemporaneous regression suggests that investor attention is primarily influenced by contemporaneous rather than lagged changes in ESG scores. In other words, changes in ESG scores appear to impact investor attention primarily within the same year rather than with a one-year lag. Across the proxies, the overall R-squared values are generally very low (or even negative in some cases), the same as in the previous part. This implies that the regression model when including controls for market capitalization and yearly return, captures only a very small fraction of the variation in both investor attention and sentiment proxies. On average, the R-squared values decreased relative to those of the contemporaneous model, suggesting that contemporaneous changes in ESG scores more effectively explain variations in investor sentiment and attention.

This regression equation was designed to ensure that the relationship between ΔESG_SCORE and investors' sentiment and attention is captured, even in scenarios where investors or the media respond with a time lag. Such delayed reactions are common in reality due to the time required for market participants and media to process and interpret new information, particularly for factors such as ESG performance. However, the results do not support this hypothesis, indicating that the relationship is primarily contemporaneous, with limited evidence of delayed effects.

Table 8 and Table 9 show the result of contemporaneous panel regression on the Sector level.

	Equation 2 Regression Result on Attention Proxies on the Sector level					
	Google Trend	Volume / Outstanding shares	Log Number of Trades	Edgar Logs	Twitter Publication Count	Number of Media Mention (Repetition)
Intercept (β_0)	-193.62*	45.545	16.389*	-8309.4	-475.41	-19.425
T-stat	-1.9653	1.501	1.9950	(1.3240)	(1.1187)	(0.3189)
Proxy Coefficient (β_1)	0.1392	-0.0581	0.0139	14.098	-1.5422	-0.3942*
T-stat	0.437	(0.6578)	0.5748	0.9459	(1.1222)	(2.0012)
R-squared (Overall)	0.0126	0.0284	0.0333	0.3964	0.051	0.1536
R-squared (Between)	0.2951	0.0015	-0.0594	0.2649	0.1616	0.0893
R-squared (Within)	-0.0945	0.0852	-0.1639	0.5325	-0.2225	0.2112
No. Observations	61	60	58	33	61	61
Included effects	Entity, Time	Entity, Time	Entity, Time	Entity, Time	Entity, Time	Entity, Time
	* 10% Significance, **5% Significance, ***1% Significance					

Table 8) This table presents the results of the coefficients from [Equation 2](#) regression on the sector level for investor attention proxies. Each regression is conducted independently for a single proxy. All variables in this equation are contemporaneous, meaning they correspond to the same year (t).

	Equation 2 Regression Result on Sentiment Proxies on the Sector level	
	News Head Daily Average	Media Sentiment (12,000 news articles)
Intercept (β_0)	0.078***	0.549***
T-stat	3.4825	11.919
Proxy Coefficient (β_1)	-0.0075	-0.0050
T-stat	-1.1296	(0.3649)
R-squared (Overall)	0.0655	-0.0278
R-squared (Between)	0.036	0.0721
R-squared (Within)	0.0698	-0.1192
No. Observations	61	60
Included effects	Entity, Time	Entity, Time
	* 10% Significance, **5% Significance, ***1% Significance	

Table 9) This table presents the results of the coefficients from Equation 2 regression on the sector level for investor sentiment proxies. Each regression is conducted independently for a single proxy. All variables in this equation are contemporaneous, meaning they correspond to the same year (t).

The results presented in Table 8 and Table 9 show the regression equation where all variables are analyzed in the same year but at the sector level. Compared to the stock-level analysis, at the sector level, only the *Number of Media Mentions (Repetition)*, an attention proxy, is statistically significant at the 10% level. Similar to the stock-level results, the negative coefficient for the *Number of Media Mentions (Repetition)* proxy, suggests that sectors experiencing declines in ESG scores tend to attract increased media coverage. The low overall R-squared values for most proxies indicate that the model (even after including control variables such as log(Mcap) and yearly return, intended to account for investors inherently paying greater attention to high-market-cap stocks or stocks experiencing significant returns) explains only a small portion of the variability in investor attention at the sector level. The difference between R-squared within and between is more pronounced here compared to stock level due to the fact that data is more limited (12 sectors and 5 years) making the result more volatile.

Neither of the sentiment proxies (News_head_avg_sent and Media Sentiment (*12,000 news articles)*) displays a statistically significant association with the change in ESG score. Thus, the contemporaneous relationship between ESG performance changes and measures of investor sentiment at the sector level is not supported by these results.

At the sector level, aggregating stock data theoretically smooths out idiosyncratic noise inherent in individual firms. However, the observed overall R-squared values remain low, indicating that the model still explains only a limited portion of the variability in investor attention and sentiment proxies. This higher R-squared indicates that a greater proportion of the variation in the dependent variables is explained by systematic factors rather than firm-specific anomalies. Consequently, sector-level analysis more clearly isolates the relationship between ESG score changes and the proxies for investor attention or sentiment. However, despite this improvement, the overall R-squared value remains low, suggesting that even after bundling stocks into sectors, a substantial portion of the variation is still not captured by the model.

Tables 10 and Table 11 show the result of panel regression on the sector level but on the Lagged series of ΔESG_SCORE.

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	Equation 3 Regression Result on Attention Proxies on the Sector level					
	Google Trend	Volume / Outstanding shares	Log Number of Trades	Edgar Logs	Twitter Publication Count	Number of Media Mention (Repetition)
Intercept (β_0)	-226.54*	69.055**	9.3956*	-2429.9	-338.2	14.254
T-stat	-1.8527	2.068	1.9326	(0.2032)	(0.8105)	0.1964
Proxy Coefficient (β_1)	-0.4166	0.1072	0.0176	-29.672	-1.7222	-0.5582**
T-stat	-1.0837	1.0777	1.214	(1.1892)	(1.3128)	(2.4466)
R-squared (Overall)	-0.0684	0.0508	0.1362	0.2189	0.0241	0.0609
R-squared (Between)	0.3376	-0.0191	0.0732	0.0892	0.1176	-0.0753
R-squared (Within)	-0.0991	0.2085	0.294	0.5017	-0.1707	0.1981
No. Observations	49	48	47	22	49	49
Included effects	Entity, Time	Entity, Time	Entity, Time	Entity, Time	Entity, Time	Entity, Time

* 10% Significance, **5% Significance, ***1% Significance

Table 10) This table presents the results of the coefficients from Equation 3 regression (lagged version of ΔESG_SCORE) on the sector level for investor attention proxies. Each regression is conducted independently for a single proxy. In this equation, the ΔESG_SCORE is lagged by one year, while all other variables remain contemporaneous, corresponding to the same year (t).

	Equation 3 Regression Result on Sentiment Proxies on the Sector level	
	News Head Daily Average	Media Sentiment (12,000 news articles)
Intercept (β_0)	0.0718***	0.5297***
T-stat	2.8563	11.438
Proxy Coefficient (β_1)	-0.007	0.002
T-stat	-0.919	0.1428
R-squared (Overall)	0.0371	0.0065
R-squared (Between)	-0.0495	-0.0239
R-squared (Within)	0.0485	-0.0093
No. Observations	49	48
Included effects	Entity, Time	Entity, Time

* 10% Significance, **5% Significance, ***1% Significance

Table 11) This table presents the results of the coefficients from Equation 3 regression (lagged version of ΔESG_SCORE) on the sector level for investor sentiment proxies. Each regression is conducted independently for a single proxy. In this equation, the ΔESG_SCORE is lagged by one year, while all other variables remain contemporaneous, corresponding to the same year (t).

The results presented in Table 10 and Table 11 reflect the panel regression at the sector level, using lagged ΔESG_SCORE as the independent variable. Among the attention proxies, the *'Number of Media Mentions (Repetition)'* proxy (β1) is statistically significant at the 5% level, indicating that lagged series of ΔESG_SCORE are associated with investors' attention and media coverage. The statistical significance of *'Number of Media Mentions (Repetition)'* in this regression equation is higher than the contemporaneous regression equation, which may indicate that media attention tends to respond more strongly to ESG score changes with a time lag, reflecting delayed reactions or prolonged discussions surrounding ESG trends and changes in the market. Moreover, same as the previous contemporaneous results, The negative coefficient (β_1 = -0.5582) indicates that sectors experiencing declines in ESG scores in the prior year tend to receive increased media coverage.

For other attention proxies and both sentiment proxies, the coefficients fail to reject the null hypothesis (β_1=0), implying no evidence of a delayed relationship between ESG performance and investors' sentiment or other measures of attention at the sector level. These findings suggest that at the sector level, media attention, as captured by the *Number of Media Mentions,* is responsive to past changes in ESG scores, while other aspects of investor behavior remain unaffected.

Moreover, overall, R-squared values remain low and decrease on average compared to the contemporaneous model, indicating that even at the sector level—where aggregation helps to smooth out stock-level idiosyncratic noise—the model explains only a small fraction of the variation in investor attention and sentiment. Additionally, introducing a one-year lag generally reduces the model's explanatory power relative to the contemporaneous model, as indicated by lower average R-squared values. The limited sample sizes (ranging from 22 to 49 observations) further underscore the caution needed in interpreting these results, as the number of data is limited.

In conclusion, the analysis reveals a consistent yet limited association between changes in ESG scores and proxies for investor attention, with no corresponding relationship observed for investor sentiment. Across both stock-level and sector-level analyses, a negative relationship is evident—firms or sectors experiencing declines in ESG performance tend to attract greater attention, as evidenced by statistically significant effects in proxies such as Twitter Publication Count (*Twitter_pub_cnt*) and Number of Media Mentions (*Repetition*). This finding aligns with what was seen in studies by Fang and Peress (2009) and Meng et al. (2023), which show that heightened scrutiny follows adverse ESG developments. Notably, the contemporaneous models (both on the sector and stock level) demonstrate stronger explanatory power than the lagged models, suggesting that investors and media react more immediately to ESG score changes rather than with a delay. However, the overall low R-squared values across all models are low which is consistent with observations on market complexity and the influence of myriad other factors on investors' attention as mentioned by Di Luo (2022) and also by Ouchen (2022)—indicating that changes in ESG scores account for only a small fraction of the variation in investor behavior. These results underscore that while ESG performance is linked to certain aspects of investor attention—particularly media coverage—the effect is modest, and ESG score changes show no statistically significant relationship with investor sentiment according to the sentiment proxies used in this study and many other factors that explain investors' attention.

6 Conclusion

ESG investing has emerged as a prominent trend, attracting significant attention from both retail and institutional investors. Many institutional investors now employ dedicated ESG teams to analyze companies' ESG scores as part of their investment decision-making process. The relationship between ESG scores and stock performance has been widely studied in the asset pricing literature. Some studies identify a positive association between ESG scores and stock returns, others report no significant relationship in the short run or in specific market contexts. Some research even suggests a conditional relationship; for instance, Ardia et al. (2022) demonstrate that in times of global concern for environmental issues, the demand—and subsequently the prices—of green stocks increase. Similarly, some papers in the corporate finance literature indicate that companies with higher ESG scores are perceived as less risky, resulting in a lower cost of capital (Sharfman et al., 2008). However, while most studies focus on linking ESG levels to corporate or asset pricing characteristics, very few have addressed the more fundamental question of whether there is a relationship between investors' attention and sentiment toward a stock and the changes in its ESG score.

In this study, various proxies commonly used in the literature were chosen to gauge investors' attention to stocks, and an NLP technique was employed to construct a variable that measures investors' sentiment toward a stock. In the literature, different LLM models have been used to calculate sentiment scores but, in this study, similar to older researches, FinBERT—a pre-trained NLP model—was used here to extract sentiment from textual data for reproducibility purposes.

For some proxies, the statistical tests fail to reject the null hypothesis (β_1=0), indicating no significant relationship with ESG score changes (*ΔESG_SCORE*). However, in the contemporaneous model, the Number of Media Mentions (*Repetition*) proxy, derived from 12,000 news articles using NLP, and Twitter Publication Count *(Twitter_pub_cnt)*—both proxies of investors' attention—exhibit statistically significant relationships with *ΔESG_SCORE*. Both of these relationships have a negative coefficient (β_1<0). These findings indicate that positive changes in ESG scores in stocks are associated with lower investors’ attention and vice versa. In contrast, no significant relationship was found between changes in ESG scores and investors’ sentiment, highlighting a disconnect between ESG performance and Investors’ sentiment.

When this methodology was applied at the sector level—which is important for many institutional investors who make decisions based on broader market segments instead of individual stocks—the Number of Media Mentions (*Repetition*) proxy continued to show a significant relationship with both contemporaneous and lagged changes in ESG scores, confirming that media attention is influenced by both current and past ESG performance albite the statistical significance of this relationship is lower compared to the stock-level analysis.

For the lagged analysis at the stock level, the relationship between ESG score changes and attention proxies is of weaker statistical significance and with a different nature. Two significant proxies are *Log Number of Trades* which is significant at 5% level and *Volume / Outstanding shares which is significant at 10%*. This suggests that while the two attention proxies of *Twitter Publication Count* and *Repetition* which mostly represent media attention lost significance, another two proxies that show trading activity became significant. This potentially shows that changes in the ESG scores are reflected in the media in the same year but investors act on this information with a one-year time lag as shown by an increase in trading activity.

Overall, the low R-squared values across all models indicate that changes in ESG scores explain only a small fraction of the variation in investor attention, implying that many other factors drive investor behavior and *ΔESG_SCORE* is not the main factor. Notably, when the analysis is conducted at the sector level—where stock-level idiosyncratic volatility is smoothed out—the R-squared values tend to increase, suggesting a somewhat stronger relationship. In contrast, when using a lagged specification instead of the contemporaneous model, on average the R-squared values decrease, indicating that contemporaneous changes in ESG scores better explain investor attention than lagged changes. Thus, with the use of these proxies, we can only assert a limited relationship between ESG performance changes and investor attention, while much of the variability remains unexplained.

These findings contribute to the limited literature on how ESG trends shape investor behavior whether investors' attention or sentiment. Specifically, the findings reveal a negative relationship between changes in ESG scores and investors' attention, meaning that investors tend to pay greater attention to stocks experiencing a decline in ESG scores. This relationship is more pronounced at the stock-level and is primarily observed within the same year in the media proxies and in the trading activity in the following year. Conversely, no significant relationship was identified between changes in ESG scores and investors' sentiment, underscoring the disconnect between ESG performance and sentiment metrics.

This study has several limitations that should be addressed in future researches. First, FinBERT's restriction to processing a maximum of 512 tokens per news article may have excluded valuable content from longer articles, potentially impacting sentiment analysis. Second, the scope of the proxies used was limited. For example, proxies such as the number of Robinhood trades or holders—which could better capture retail investor interest—are no longer publicly accessible, limiting the scope of the analysis. Finally, the annual frequency of ESG data for some stocks reduces the ability to capture more dynamic relationships; higher-frequency data would provide deeper insights and improve the robustness of future studies.

Future research could expand on these findings by addressing several key areas. First, isolating positive and negative shocks to changes in ESG scores could offer a more detailed understanding of how investors and the media react to different directions of ESG performance. Second, leveraging data from *Stocktwits*—a platform specifically tailored to financial discussions— or trading activity from Robinhood could enable a more targeted analysis of investor sentiment and attention because these platforms are predominantly used by retail investors. Conducting both *repetition* and sentiment analysis on *Stocktwits* data would complement existing proxies and offer insights into the behavior of retail investors. Enabling to split and analyze the reaction of institutional and retail investors independently. Lastly, advancements in large language models (LLMs) such as ChatGPT present an opportunity for enhanced sentiment analysis compared to current pre-trained models like FinBERT. Deriving a sentiment proxy using LLM models and on more comprehensive data could serve as a better proxy for investors' sentiment.

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Appendix A

Average sentiment for each sector during the period of study

Sector	Average Sentiment
Basic Materials	0.49
Communication Services	0.28
Consumer Cyclical	0.42
Consumer Defensive	0.55
Consumer Discretionary	-0.28
Consumer Staples	-
Energy	0.45
Financial Services	0.63
Healthcare	0.47
Industrials	0.45
Real Estate	0.76
Technology	0.44
Utilities	0.63

Table 12) This table shows the average sentiment of all the stocks in a given sector through 2018-2023.

Appendix B

Average number of news coverage for stocks of each sector. For instance, stocks within the 'Financial Services' sector are mentioned, on average, in 10.07 articles out of the 12,000 news pieces analyzed over the six-year research sample.

Sector	Average Number of Covering News (repetition)
Basic Materials	0.48
Communication Services	1.48
Consumer Cyclical	0.56
Consumer Defensive	0.64
Consumer Discretionary	0.14
Consumer Staples	-
Energy	2.61
Financial Services	10.07
Healthcare	0.82
Industrials	0.83
Real Estate	0.44
Technology	0.84
Utilities	0.50

Table 13) Average number of news articles covering stocks in each sector. This metric represents the frequency with which stocks from a given sector appear in the dataset of 12,000 news articles collected over six years.

Appendix C

Sector	F.E. Google Trend	F.E. volume turnover	F.E.s log Number of Trades	F.E. Edgar logs	F.E. Twitter Publication Count	F.E. News Head Average sentiment	F.E. News Repetition	F.E. News Sentiment
Basic Materials	28.95	1.20	-0.16	-326.28	-97.41	-0.33	-6.66	-0.04
Communication Services	-45.31	-18.78	1.40	-17.20	389.52	0.06	4.41	-0.56
Consumer Cyclical	39.55	102.00	2.29	-338.79	256.57	0.01	-11.48	-0.35
Consumer Defensive	12.67	-24.89	1.45	-216.71	-128.85	-0.12	-11.39	-0.04
Energy	-13.28	-23.55	1.14	244.27	-72.85	-0.55	5.23	-0.05
Financial Services	-9.62	-16.00	-1.33	394.96	-95.02	-0.02	43.45	0.69
Healthcare	-33.14	20.54	-1.88	-321.56	-45.70	0.29	-5.19	0.16
Industrials	11.49	5.87	-0.73	-138.16	-48.32	-0.21	-5.83	-0.19
Real Estate	42.90	-17.91	-1.87	-312.55	-97.11	0.93	-2.07	1.26
Technology	-43.27	8.32	0.87	1418.29	67.95	-0.14	-2.20	0.09
Utilities	20.82	-29.06	-1.18	-386.28	-125.17	0.15	-7.26	0.52

Table 14) This table shows the value of the Fixed Effect in the regression equations, separated by each sector.