Are ESG Improvements Recognized? Perspectives from the Public Sentiments*

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Abstract

Environment, Social, and Governance (ESG) have caught the attention of many investors, managers, and academic researchers in the domain of investment management. However, there have been limited perspectives about the public, which is arguably the biggest shareholder of corporate ESG. The public's perceptions and volumes shape the demands and standards for ESG in the investment management sector. Thus, a critical question arises: Does the public absorb information about the changes in public companies' ESG performance and calibrate their sentiments accordingly and timely? Given the highly turbulent nature of ESG and the difficulty of measurement, ESG sentiments and related portfolio decisions are heavily affected by the taste and attention of the public. I take a critical first step to understanding these problems by proposing a new proxy for the public's attention and sentiments on public companies after a de facto change in companies' ESG performance. I study how the public perceives the changes in corporate ESG performance by constructing a combined quarterly panel of Environment, Society, and Governance metrics and public ESG sentiments of S&P 500 constituent companies from X (previously known as Twitter) from 2010 to 2021. I find empirical evidence for a significant cognitive lag of the public sentiments after changes in firms' ESG performance, which is heterogeneous across different sectors. I conclude with a further discussion of portfolio management and social implications.

JEL classification: G12, G39, G42. **Keywords**: ESG, public sentiments, sustainable investing, social media, X(Twitter), attention lag.

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1 Introduction and Motivation

Companies, especially publicly listed companies, nowadays pay attention to ESG profiles. In the past decade, public companies around the world have been gradually rebranding traditional notions such as corporate social responsibility or social entrepreneurship as environment, social, and governance (ESG). Many companies have spent substantial budgets and efforts in improving their ESG profiles and branding themselves. This is known as 'greenwashing'.

As the landscape in ESG branding has become increasingly popular and competitive, investors have also begun to pay attention to this area. The prior sustainable investing literature, such as Pástor et al., 2021 and Berg, Heeb, et al., 2022, has verified that retail and institutional investors tend to tilt their portfolios towards their ESG preferences and often pay a premium to hold 'green assets' that do well in the ESG space. Conceptually, there can be a couple of reasons why institutional and individual investors chase ESG assets. They derive personal utility from investing in ESG initiatives, believe that ESG initiatives will increase firm value, or are in the public eye and use ESG to increase their reputation. Lioui and Tarelli, 2022 document that ESG factors are used in alpha construction. On the other hand, some investors are using ESG factors as hedges for risks (Engle et al., 2020).

Regardless of the motivations, the investors need to follow the ESG profiles of stocks closely to align their investment strategies with objectives. However, as documented in prior literature, the ESG ratings may keep changing and the measures of ESG scores can be noisy.

What has not been studied is whether the public and investor community can cognitively perceive the changes in the ESG profiles of public companies. This paper studies two empirical questions: 1. Is there a gap between the change in the public's sentiments on public companies and the actual change in the companies' ESG performance? 2. Does a change in a company's ESG ratings predict a lagged change in public sentiments toward that company?

My key finding is that while the public can recognize the improvements or declines in ESG performance of the companies, this happens with a lag of one to two quarters. After taking out the time and industry invariant characteristics, the environment, social, and governance variables from the previous quarter are consistently significant and explain the sentiment changes better than the contemporaneous environment, social, and governance variables. We discover that empirically an improvement in social and governance ratings predicts a positive sentiment shift, and an improvement in environment ratings predicts a slightly negative sentiment shift. This is likely because the public could perceive the publicly listed companies' social and governance better but may not have the expertise or attention to appreciate corporate efforts in environmental agenda or identify environmental greenwashing stories. Since there's no controlled experiment setting, one can argue that other latent variables such as public attention, managerial competence, or company policy stability impact the firm's public sentiments. I use alternative data sources such as Ravenpack Equities 4.0 data to proxy for these variables and control for their impact in my model.

The further asset pricing question is whether the lagged sentiment signals forecast returns of specific companies. I introduce a theoretical model of an attention-constrained Retail Investor making the stock selection and weighting decisions under ESG profile changes in two periods. Intuitively, a retail investor pays heterogeneous attention to different stocks due to differences in personal favors, exposure from social and financial media, and strategies. Some stocks get more attention and some get less. This could be easily seen from the significant differences in the trading volume of retail investors.

When there is a change, either positive or negative, in the ESG profile of a firm that the investor pays more attention to, the investor is more likely to notice the change and better gauge the influence on the stock prices. Simply, the investor is more likely to observe the stock returns in the next period timely and calibrate their positions more quickly. The reverse is true for the low-attention stocks. Consequently, a retail investor with limited attention may overreact in adjusting the weights of the higher-attention stocks and underreact in adjusting the weights of the lower-attention stocks. Retail investors in aggregate would deviate from their pre-determined optimal portfolio over time. In aggregate, this may give rise to the opportunity of some excess return opportunities in low-attention and large-ESG-change stocks.

My findings with the sentiment lag pattern give some empirical support to the grounds of this above mechanism about retail investors' attention limit. That said, this paper also supplements the ESG factor literature, previously documented as a 'Greenium' in Pástor et al., 2022, and the rising literature on how ESG investing shapes prices' information aggregation brought by Goldstein et al., 2022.

To summarize, I contribute to the sustainable finance literature by theorizing the behavioral implications of attention limits and public sentiments on companies in the ESG space. The connection between ESG performance change and public sentiments arose recently and will remain pertinent for a long while. This sentiment and return predictability will reaffirm the public companies' commitment to being socially responsible and sustainable in the long run.

2 Hypothesis on Attention and Sentiments

Based on the following assumptions, this paper's propositions are empirically testable hypotheses.

Assumption 1: Investors have limited attention.

I follow the common foundational idea in behavioral finance that the public and investors, either individual or institutional, have limited attention and make decisions about their portfolio investments within that attention constraint. Even at prominent hedge funds, each analyst tends to cover very few stocks in a specific sector. Edmans et al., 2022 summarizes that investor sentiments, characterized by exogenous shocks to the sentiments, can significantly influence stock returns. In addition to the asset pricing implications, public sentiments may shed light on the effectiveness of public companies' focal agenda of branding themselves. Some 'brown' companies, which means less environmentally friendly and sustainable and not 'green', may promote themselves tirelessly on traditional and social media such that the public's views may deviate from reality. Some companies in traditionally 'brown' sectors (such as petroleum companies) may have improved their ESG performance but did not proactively promote their public image or successfully communicate to the public about their improvements. Consequently, the public and investors who are concerned about ESG issues may not recognize the change in ESG performance when evaluating their investment decisions and constructing their portfolios.

Thus, this poses an important question to practitioners of the finance industry and academic researchers: Do the changes in the ESG profiles of the publicly listed companies matter for the social and public sentiments on them? To answer the questions, here are the additional hypotheses:

Hypothesis 2: With limited attention, the public and investors may still observe the change in ESG performance, though ESG might just be a class of secondary considerations in addition to standard investment metrics.

Under this hypothesis, I propose the following investor sentiments model:

$$ST_{i,t} = \alpha_{i,t} + Z_{i,t} + \beta_1 E_{i,t} + \beta_2 S_{i,t} + \beta_3 G_{i,t} + u_{i,t} \tag{1}$$

$ST_{i,t}$ denotes the public sentiment on firm i at specific quarter t. $Z_{i,t}$ denotes the whole set of other explanatory variables concerning the company characterizing the traditional sentiments on the company's financial profile, including managerial potential or abilities. I choose to break down environment, social, and governance as three different explanatory variables instead of using one compound ESG score to be able to accurately model the influence of exogenous shocks on one of the three pillars. While these three pillars usually correlate, they are adjusted in response to different signals. Given the difficulty of surveying the public massively and persistently on their sentiments and the lack of representativeness, this paper proxies the English-speaking public's sentiments on public companies creatively with tweets. Recent literature has made some initial attempts to capture investor attention from social and financial media. For example, Cookson et al., 2022 use social media (StockTwits) to see social media sentiments' influence on corporate M&A decisions. Goloshchapova et al., 2019 use reports from Bloomberg to extract corporate social responsibility topics discussed. Sentiment signals may disclose critical corporate information, as reported in Green et al., 2019.

Relative to other social media, Twitter is more reflective of public sentiments due to its several advantages: First, Twitter has the advantage of being accessible to everyone and popular globally but not limiting itself to the investor community. Second, Twitter is updated at the rate of 500 million every day and can be easily categorized around one company. Third, there has been a tremendous number of posts from a large pool of representative users on Twitter since 2006, which provides a satisfactorily long panel. The related benefit is that the number of tweets for even the less discussed stocks in S&P 500 is also large. For the sake of sentiment analysis, Twitter is also better than alternative proxies like the number of Google searches or Bloomberg terminal searches in a given period. This type of search may only reflect attention and is usually rather neutral, as it only serves to query the information about ongoing events. But what this paper needs are concrete sentiments that can be analyzed from a sentence-based linguistic context.

Given all these advantages, I can construct a fairly proxy sentiment index that's updated constantly and reflective of the broader public by constructing the weighted sentiment scores [1] of Twitter posts.

I use the natural language processing package, NLTK Vader, to construct a time series for compound sentiment scores for each ticker. The raw compound sentiment score is scaled to the range of $(-1, 1)$, with 1 indicating the tweet is most positive and -1 indicating the tweet is most negative. Since the more popular tweets (more replies, more followers, more likes) capture the more popular sentiments, then we assign higher weights to these tweets' sentiments. I use the following formula to generate the weighted scores. In the following formula, the weighted sentiments $\text{sentiment}_{\text{weighted}}$ and raw sentiments $\text{sentiment}_{\text{raw}}$ are denoted as ST_w and ST_r. And ST_r is computed by the NLTK Vader compound sentiment score. R is the number of replies to that tweet, and L is the number of likes of the tweet, and F is the number of followers of the account.

$$ST_w = ST_r * (R + L + F^{0.5}) \tag{2}$$

The goal of this weight adjustment formula is to represent the impact of overall sentiments more accurately. People converse with others on Twitter by not only posting but also giving likes or responding to others' tweets. More popular tweets tend to capture more attention and

[1] Please refer to the appendix for how the sentiment score is constructed. It is the weighted average of NLTK Vader Wagner, 2010. Natural Language Processing with Python. O'Reilly Media Inc. https://www.nltk.org/book/) polarity compound sentiment score of each tweet in that quarter

better represent the aggregate public sentiments. Empirically, the square root of follower counts has the same magnitude as ReplyCounts and LikeCounts. Thus, I use the square root instead of taking the Log of FollowerCounts for a more fair representation. Despite so, picking the square root or the log of the the like counts has limited impact on the results of this paper, because most of the variations come from the sentiments of the tweet.

Furthermore, the calculation of weighted sentiments loop through all of the tweets and tweets responding to them. This avoids concerns that arise from a hypothetical situation, where a thought leader posts a tweet with positive environmental sentiments on the firm A and gets strongly criticized by many responding posts with negative environmental sentiments on the firm A. In this circumstance, both the positive sentiments and negative sentiments are considered in the aggregation process. Besides, if there are many strongly objecting to the thought leader's view, they may as well post or respond to posts of another thought leader who holds opposing views. This is why the proposed weighting mechanism is a valid approach to construct the aggregate sentiments, which is then representative of the public sentiments on the firms.

Hypothesis 3: ESG shocks influence the public and investor's sentiments in aggregate.

In thinking about how the public sentiments toward the firms would change when ESG ratings move, there are two potential challenges. First, when a company does well (or poorly) in the ESG space, it may be due to an improvement in unobserved features such as managerial or board talents. This could make the financial performance and ESG profile improve at the same time, which is essentially an outward shift of the Pareto curve of the ESG and profit tradeoff. Then the ESG ratings may not necessarily reflect the increased corporate efforts and commitment for ESG.

Second, the stickiness or volatility of the public sentiments tend to differ depending on the sector. For example, even as Shell Global has stated that they are navigating the energy transition by lowering carbon emissions, increasing investments in renewable energy sources, and launching many initiatives to help the environment and local community, a portfolio manager or an equity research analyst of an ESG-minded fund may consider it the opposite of a green firm. As reported in the popular press like the Wall Street Journal [2], Shell has been promoting its corporate identity by accelerating to become a net-zero emissions energy business in 2021, whereas the green investors were still not attracted.

My approach deals with both of the challenges with the following procedure. I explain how to tackle the first challenge in Regression 3 under Section 4. I tackle the second challenge via fixed effects. For company c of industry i at time t, I include industry fixed effects to remove the time-invariant characteristics within the same industry. Presumably, S&P 500 companies in the same industry (such as Apple and Alphabet in Communication Services, Morgan Stanley and Goldman Sachs in Financials, or PepsiCo and Coca-Cola Company in Consumer Staples) have similar levels of public and investor attention, because their businesses are highly related and investors have them on the watchlist at the same time. I also include time fixed effects for each quarter to account for the potential underlying sentiment cycles across time.

3 Descriptive Statistics, Data, and Empirical Analysis

I acquire multiple the original data sets from various sources.

3.1 Social Media Sentiments Data.

Twitter is an open social network for people to converse with each other, and the messages on Twitter are known as tweets, growing at the speed of 500 million tweets every day.

To construct a sentiment series, I choose Tweets related to S&P500 companies. I use the cash tag plus ticker as identification to pull the related tweets from 2010 to 2021 about every individual company. Any tweet that mentions the company will be identified and downloaded by year.

I clean all the Tweets by removing those lines that are (i) not in English. (ii) not constitute full sentences for sentiment analysis. (iii) duplicate tweets from the same Twitter account. In this procedure, we also access the number of followers of the account for each

[2]See the report here at: https://www.wsj.com/articles/shell-woos-financial-investors-not-green-ones-11643894238

post, the number of replies to each post, and the number of likes to each post to compute the sentiment weights discussed in section 2.

3.2 Stock Return Measures

I use dividend-adjusted stock returns as the return measure. Stock price data is available from CRSP (Center for Research in Security Prices) using WRDS access [3]. From the raw monthly dividend-adjusted stock return data provided, I compute the unannualized quarterly dividend-adjusted return in that quarter. The period studied by this paper starts from 2010, which avoids the aftermath of the 2008 financial crisis and subsequent recovery. In case there is missing data for any specific company, we use the average return of nearby quarters to fill the panel. I run two versions of my model: one with missing data, and one without missing data.

3.3 ESG Ratings

While Jacobs and Levy, 2022 and Avramov et al., 2022 have documented some disparities in Environment, Social, and Governance (ESG) ratings across various rating agencies, there is a common underlying agreement of what features count as better in ESG. The metrics are different because the rating agencies have an inherent motivation to make their ESG ratings distinct to differentiate themselves. Thus, the correlation in ESG ratings is very high despite differences in the metrics. According to the systematic analysis of all ESG ratings reported from Berg, Kölbel, et al., 2022 and Berg, Heeb, et al., 2022, the MSCI and Sustainalytics ratings are the most comprehensive and least noisy. MSCI provides annual ratings and component ratings since 1991 [4], whereas Sustainalytics provides monthly ratings and component ratings since 1991 [5]. While the database is growing fast, these two ratings follow a rigorous methodology that does not make ex-post adjustments to their ratings. This prevents the potential bias of making artificial correlations with stock performance. In this paper, I assume that these two rating agencies do not suffer the limited attention that individual investors do and trust their methodologies.

[3]https://wrds-www.wharton.upenn.edu/data-dictionary/crsp_ m_stock/. accessed 2022-8-17

[4]https://wrds-www.wharton.upenn.edu/pages/about/data-vendors/msci-formerly-kld-and-gmi/, MSCI methodology descriptions from Wharton Research Data Services, accessed 2022-8-17

[5]Sustainalytics methodology descriptions from Wharton Research Data Services, accessed 2022-8-17, https://wrds-www.wharton.upenn.edu/pages/about/data-vendors/sustainalytics/.

One potential caveat is that the public sentiments on ESG may have fewer variations in the earlier years in the panel, since the formal notion of ESG has entered the public horizon only in the past decade. However, the value propositions of ESG and some keywords associated with it, such as 'anti-pollution','responsible management', 'fair salary', and 'sustainable local community responsibility', have existed for a long time and were previously known as corporate social responsibility.

3.4 Industry Classification Industries in general serve the same functions in the market and have similar or invariant characteristics. I want to view them as a cluster in my fixed effect models. I obtain industry definitions from Kenneth French's industry portfolios on his website [6] for all S&P 500 constituent companies.

3.5 Attention Data To proxy for investor attention, I use coverage in financial media (including blogs, journals, and paper coverages) through Dow Jones Newswires, the Wall Street Journal, and Bloomberg. Such coverage data is available from Ravenpack 4.0 Equities [7] accessed from Wharton Research Data Services. RavenPack is the leading provider of insights and technology for many hedge funds, banks, and asset managers. The raw coverage data set from 2010Q1 to 2021Q4 of Ravenpack 4.0 Equities includes a record of 18 billion coverages for more than 1700 entities (firms or social organizations). The entity names are sometimes exactly the company name listed by NYSE or NASDAQ because they can be the subsidiaries of a public company. I match these entities to the corresponding tickers in S&P500 using Jaro–Winkler metrics from Jaro, 1989 and Levenshtein metrics from Levenshtein, 1965 (see appendix for details) and manually check the accuracy for potentially unclear cases. I sum the counts for coverage for each ticker in each quarter and get a quarterly 'attention score' series.

[6] Kenneth R. French - detail for 49 industry portfolios. Retrieved September 21, 2022, from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html.

[7] Ravenpack Analytics accessed from WRDS, https://wrds-www.wharton.upenn.edu/pages/get-data/ravenpack-news-analytics-40/. Wharton Research Data Services. "WRDS" wrds.wharton.upenn.edu, accessed 2022-10-17. Ravenpack extracts name entities related information together with financially relevant events from publications that are generally observed by the investor.

4 Empirical Models of Environment, Social, and Governance Performance on Public Sentiments

Given the above theory and mechanisms, I present the following model to empirically support my theory: subscript H denotes the firms with the most positive shock and subscript L denotes firms with the most negative shocks in environment, social, and governance scores:

Regression1: Contemporary Ordinary Least Square Regression of Public Sentiments

$$ST_{i,t} = \alpha_{i,t} + \beta_1 E_{i,t} + \beta_2 S_{i,t} + \beta_3 G_{i,t} \tag{3}$$

Regression2: Industry Wide Fixed Effect Regression of Public Sentiments

$$ST_{i,t} - \overline{ST_i} = (\alpha_{i,t} - \overline{\alpha_i}) + \beta_1(E_{i,t} - \overline{E_i}) + \beta_2(S_{i,t} - \overline{S_i}) + \beta_3(G_{i,t} - \overline{G_i}) + (u_{i,t} - \overline{u_i}) \tag{4}$$

where α_i represents the set of time-invariant characteristics for industry i, and the averages of sentiment score, environment, social, and governance scores are calculated as the following:

$$\overline{ST_i} = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{C}\sum_{c=1}^{C} ST_{i,c,t}$$

$$\overline{E_i} = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{C}\sum_{c=1}^{C} E_{i,c,t}$$

$$\overline{S_i} = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{C}\sum_{c=1}^{C} S_{i,c,t}$$

$$\overline{G_i} = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{C}\sum_{c=1}^{C} G_{i,c,t}$$

Here, i is the index for the industry. Since my method requires representative online sources of sentiments, my sample comprises only the large S&P 500 public companies. I naturally face the tradeoff in picking how fine the categorization of the industry is. If the number of industry categories included is too large, then my estimators can be noisy. Another limitation is that industry categories may be controversial. For example, Amazon can be considered in the same sector as Google or Walmart, alternatively. In addition, the number of companies in each sector differs significantly.

Given the above limitations, I would prefer to use firm fixed effect as opposed to industry fixed effect in this paper. Firm fixed effect is a more stringent specification of industry fixed effect and rids of the time-invariant characteristics of a specific firm more reliably. The simplest firm fixed effect estimator follows as model 2.

Regression3: Firm Wide Fixed Effect Regression of Public Sentiments

$$(5) \quad ST_{c,t} - \overline{ST_c} = (\alpha_c - \overline{\alpha_c}) + \beta_1(E_{c,t} - \overline{E_c}) + \beta_2(S_{c,t} - \overline{S_c}) + \beta_3(G_{c,t} - \overline{G_c}) + (u_{c,t} - \overline{u_c})$$

Here, c is the subscript representing a specific company, so this regression is on every company instead of every sector. Similarly, $\alpha_c = \overline{\alpha_c}$ because α_c represents the set of omitted characteristics specific to that firm.

$$\overline{ST_c} = \frac{1}{T}\sum_{t=1}^{T} ST_{c,t}$$

$$\overline{E_c} = \frac{1}{T}\sum_{t=1}^{T} E_{c,t}$$

$$\overline{S_c} = \frac{1}{T}\sum_{t=1}^{T} S_{c,t}$$

$$\overline{G_c} = \frac{1}{T}\sum_{t=1}^{T} G_{c,t}$$

In addition, to capture the potential shocks in the interaction of industry and quarter, I include its fixed effect based on model 2.

Regression4: Firm Wide Fixed Effect Regression with Industry Quarter Fixed

Effect

(6)

$$ST_{c,t}-\overline{ST_c} = (\alpha_c-\overline{\alpha_c})+\beta_1(E_{c,t}-\overline{E_c})+\beta_2(S_{c,t}-\overline{S_c})+\beta_3(G_{c,t}-\overline{G_c})+\beta_4(Q*I_{c,t}-\overline{Q*I_c})+(u_{c,t}-\overline{u_c})$$

Every term is the same as that in Model 2, except that Q denotes quarter and I is the dummy variable for the industry.

$$\overline{Q*I_c} = \frac{1}{T}\sum_{t=1}^{T} Q*I_{c,t}$$

The fixed effect estimators should get rid of the 'cognitive stickiness' that depends on the firm or the industry.

There are two important factors, among other less important ones, that may influence the sentiments: managerial competence and investor attention. In accounting literature, managerial competence is usually proxied by Return on Assets, which is deeply correlated with stock returns in general. Since I want to study the implication of public sentiments on asset prices later, I just do not proxy for managerial competence in my regression here in the first step. On the other hand, to proxy for investor attention, I use Ravenpack 4.0 Equities Data to access the total number of media coverage (on Wall Street Journal, Dow Jones Wires). I believe that this is a better proxy than using the number of Google searches, because the search for the ticker is too specific for attention on the stock price of a company and the Google search for the full name may be too irrelevant. For example, a search for 'Walmart' may just be a search for retail purchases, not attention to corporate movements in Walmart.

Due to occasional blanks in Sustainalytics ESG scores or Ravenpack Equities 4.0, I deal with the unbalanced panel in two ways: (1) drop all the quarters with a variable missing. [8] (2) replace the missing data with the firm average for that specific series.

In this paper, I decide that using quarterly data series is optimal for two considerations:

[8] Omitting all entries with missing data is the default setting with R. I will report the regression results with both options. I don't replace missing data with the industry's average since that approximation is too coarse.

First, the public company's profile only changes quarterly by the end of each quarter as 10-Q or 10-K forms get released. Thus, there's no need to use monthly series. Second, since the notion of Environment, Social, and Governance (or previously, Corporate Social Responsibility) arose only in the past decade, I will have a short series if I use yearly data. In empirical finance literature with factor models, the typical requirement is that the number of regressors needs to be at least five fewer than the time series ($K \leqslant T-5$). Using quarterly frequency data on my data set enables us to make T bigger than 30.

Hypothesis 5: Investors may observe changes in ESG performance of each company over time. However, due to the limitation of their attention, the environment, social, and governance scores will be lagged indicators for changes in investors' sentiments.

This is an easily testable hypothesis. Since the professionals at rating agencies have an extensive background in economics and statistics as well as expertise in corporate governance, it is fair to assume that the ESG ratings capture the firms' changes in ESG performance timely and accurately. In contrast, with limited attention and expertise, the general public will absorb the information from incomplete information channels, such as News, social media, and investment reports more slowly and gradually. In the long run, they will observe the changes of the firms' performance in the ESG space and calibrate their views accordingly. This cognitive gap between sentiments and reality may ultimately lead to the predictability of stock prices. I will test this hypothesis by including different numbers of lagged explanatory variables to account for potential autocorrelation in the public sentiments of a certain firm.

Thus, I contribute to the intersection of sustainable investing and investor attention literature in two ways: (1) I theorize the behavioral implications of attention limits and public ESG sentiments on firms and test the robustness of the link with empirical evidence for more than a decade (Since 2009). (2) Given this gap, my findings point to the asset pricing research that the ESG factors should be viewed as lagged regressors when used in predicting stock returns and constructing portfolios.

My theoretical prediction is threefold: (1) if there's a positive exogenous shock in ESG ratings (I may consider the Sustainalytics new release of the firm ESG scores, unrelated to stock performance at all according to their methodology [9], can be regarded as exogenous shock quarter to quarter), but the public sentiments haven't reflected it, there will be a short-term positive excess return opportunity because ESG-conscious investors such as hedge funds, mutual funds, and other institutional asset or wealth managers will flock to these stocks. (2) If there's a negative exogenous shock in ESG ratings and the public sentiments haven't reflected it, there will be a short-term negative excess return in that window. (3) If there's either a positive or negative exogenous shock, but public sentiments have moved in the same direction timely for whatever reason, then I predict the alpha opportunities are approximately zero empirically. I theorize this link between ESG ratings shocks and asset returns changes by attention limitations, which may vary across different sectors and firms. I suppose (3) will happen a lot more commonly in certain sectors or firms that receive a large amount of attention in investor channels and social media.

5 Main Results of Public Sentiments

Following the methods and considerations introduced in Sections 4 & 5, from empirical results (see appendix for the full tables), I find that the social score of a firm is strongly significant, whereas the environment and governance are moderately significant.

The industry invariant characteristics explain some variations of sentiments. The environment, social, and governance scores of the previous quarters are also often indicative of the changes in public sentiments. There are also a lot of quarterly invariant features that explain the aggregate public sentiments on each company. Certain quarters and industries show a pattern, but we find no cyclical pattern in quarters' influence on public sentiments. Industry fixed effects and Quarter*Industry fixed effects are sometimes significant.

When I include one quarter or two quarters of lagged environment, social, and governance variables into the model, they are significant but the contemporaneous environment, social, and governance variables become no longer significant. This confirms our theory that the public takes time to digest information from the media and adjust their perceptions on firm ESG profiles, especially for the firms and industries that receive less investor and

[9] sustainalytics.com.2022. ESG Risk Ratings, Available at https://www.sustainalytics.com/esg-data, Accessed 21 September 2022.

public attention. The previous quarter's ESG performance in general plays a greater role in influencing public sentiments. The degree of sentiment lag tends to be around one to two quarters for the public.

We observe that when we include only the environment, social, and governance variables from the last quarter, the social score from the last quarter is significantly positively correlated with public sentiments this quarter, whereas the social score this quarter tends to be negatively correlated. The same holds for the governance score variable. The environmental score variable displays the opposite pattern, but the magnitudes of the coefficients are much smaller. This statistically significant pattern indicates that the public in general is not able to sense the objective changes in companies' ESG profiles accurately and timely. It also indicates that the public values the social and governance aspects of the firm more and considers the environmental performance of the firm less salient. This is coherent with the findings in Pástor et al., 2022 that individual investors may not feel better about more environment-friendly stocks that provide more hedge to climate risks, since such stocks are more expensive to hold in the portfolio. My findings further suggest that this logic does not apply to stocks that perform better in social and governance aspects. This is because social and governance metrics are more closely tied to the financial metrics of a company, which makes a stock with decent performance on social and governance metrics considered 'more lucrative' but not a good hedging stock to hold.

Having used time fixed effects and firm fixed effects on the data from the most recent 48 quarters, I ensure that the relationship between public sentiment changes and changes in ESG profiles is robust. This confirms our hypothesis in the motivation that the public slowly takes information, and the sentiments converge to reflect actual profiles.

6 Alternative Explanations and Robustness Checks

Some may argue that there are some potential omitted variables here, which could lead to bias that is not ruled out by the fixed effects above. I summarize the major part of these variables: (1) Managerial competence or talents. Some companies treat ESG as a secondary concern when facing tradeoffs with financial motivations, yet they still have good ESG results. These firms could achieve so if they happen to have star managers who take good care of both. Dzieliński et al., 2022 documents evidence that high-ability managers can efficiently allocate resources and choose ESG projects to enhance shareholder value, which leads to high morale and good sentiments among the public and investors. (2) Public attention on the firm (3) Stability of corporate governance policies.

While these variables may indirectly shape the public sentiments on firms' performance in the environment, society, and governance, they do not represent de facto changes in the firm's ESG performance as captured by the ratings. Thus, it is possible to proxy for these variables respectively and empirically show that they have little effects that do not overshadow the significant influence of the objective ESG ratings.

I use a proxy for the each of above three variables and include the proxy variables in the additional regression model. Then I test the original model (partial model) against the extended full model. It turns out that empirically these alternative variables have no significant influences. This rejects the potential alternative possibilities and further validates this paper's main theory.

Mgr denotes the managerial competence/abilities (measured by ex-post ROA in accounting), Pub denotes the degree of public and investor attention (firms with more media coverage such as Tesla have higher scores)

$$ST_{i,t} = \alpha_{i,t} + Z_{i,t} + \beta_1 E_{i,t} + \beta_2 S_{i,t} + \beta_3 G_{i,t} + \beta_4 Mgr_{i,t} + \beta_5 Pub_{i,t} + u_{i,t} \tag{7}$$

Managerial or CEO competence is very hard to measure independently just from returns. It involves a complex interplay of strategic decision-making, leadership, and adaptability, which cannot be fully captured by financial returns alone, as these metrics are also influenced by external market conditions and internal factors beyond a CEO's control. Furthermore, the impact of CEO decisions on a company's performance may have a lag effect, making it challenging to directly correlate short-term returns with CEO competence. More straightforwardly, the board will fire the CEO when the firm performs badly because they straightforwardly measure managerial competence by ex-post returns on assets (ROA). Since there is not a consensus measure in prior literature, I pick my own proxy for managerial competence. As described in the data section, I quantitatively proxy for investor attention on a company by the number of appearances on financial media including Dow Jones Newswires and Wall Street Journal for every quarter. Secondly, from a practical perspective, speculative activities on certain companies' stocks do not change the ESG sentiments on firms, though it may give those companies more attention in the short term. However, this attention is already picked up by managerial talent and company publicity. Thirdly, the stability of corporate governance policies will be slowly moving across quarters and may appear more like categorical variables for specific firms.

Empirically, I find that adding the proxy attention variable does not increase the explanatory power. Attention has a zero coefficient consistently and is not significant across all regression models. This rules out the alternative story that investor attention (which I proxy by coverage in financial media) influences the changes in public sentiments toward the firms. While public sentiments tend to be correlated ex-post with returns of the firms, I conclude that changes in the environment, social, and governance performance explain a considerable non-financial part of the sentiments.

7 An Intuitive Model of Limited Attention and ESG Dynamics for Retail Investor Perceptions

In exploring the pattern of delayed public sentiment shifts subsequent to changes in ESG performance, I aim to examine the resulting effects on retail investor perceptions. Given the empirical evidence that retail investors, often lacking in sophistication, have limited attention, knowledge, and research capabilities, they might not fully perceive or understand shifts in corporate ESG performance. This lack of attention results in flawed assessments of companies' future prospects, causing investors to stray from their ideal portfolio, whether they desire a 'greener' one with higher ESG scores or a 'grayer' one with lower scores. I propose a model of a typical investor with limited attention—contrasting with a hedge fund's comprehensive coverage by full-time employees—focusing on potential shifts in the ESG profiles of stocks within their portfolio.

Model 1: Representative agent's portfolio decision under attention disparities.

A representative agent (investor) is tasked with making decisions about a stock portfolio, which includes four types of stocks categorized as follows: companies with high prior ESG performance receiving high attention (Category 1), companies with low prior ESG performance but receiving high attention (Category 2), companies with low prior ESG performance and low attention (Category 3), and companies with high prior ESG performance yet receiving low attention (Category 4).

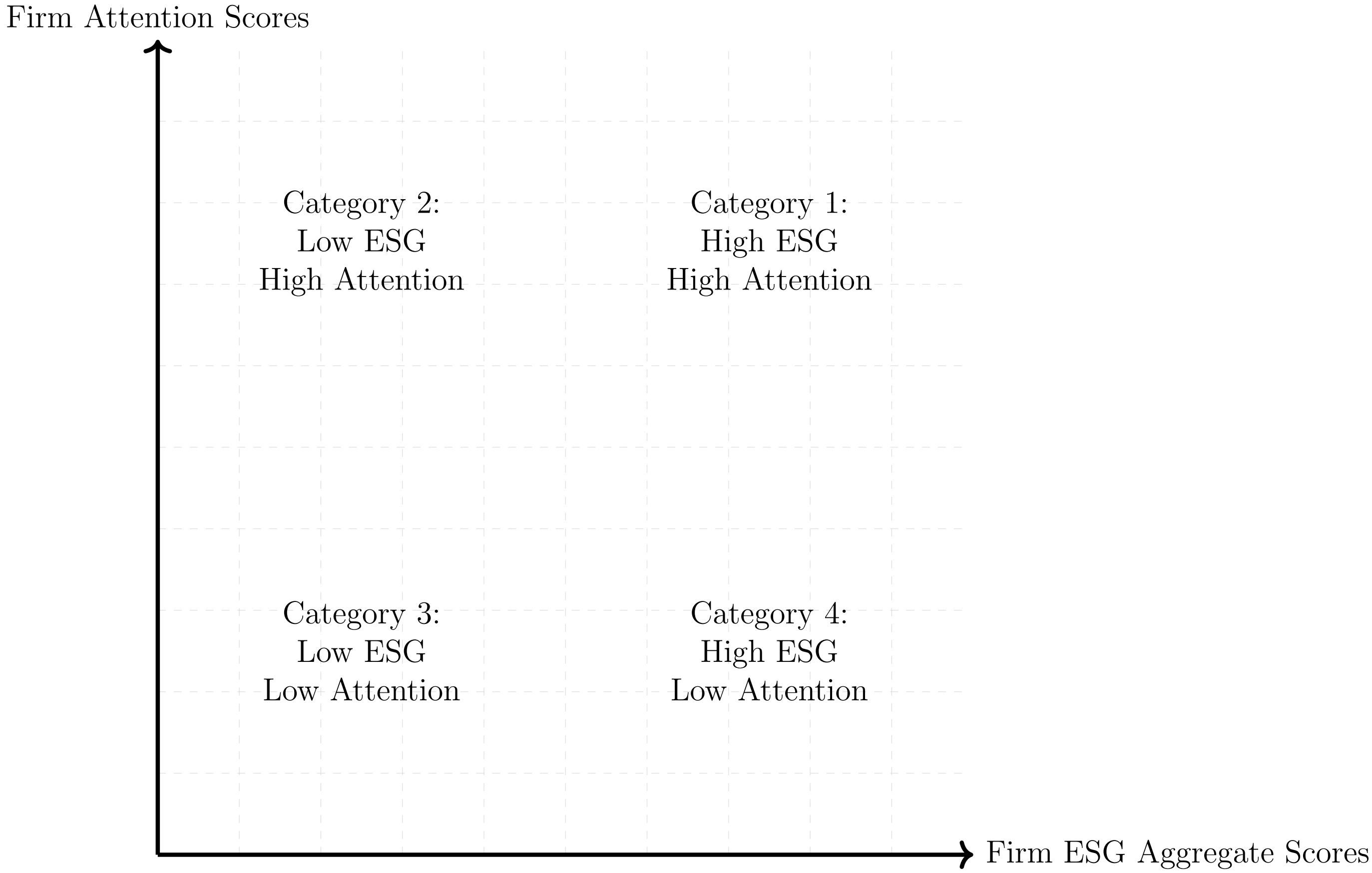

Figure 1: Stock Categories by ESG Performance and Attention Level

For illustration purpose, here is a plot of 30 representative stocks from S &P 500 and how they fall under each category.

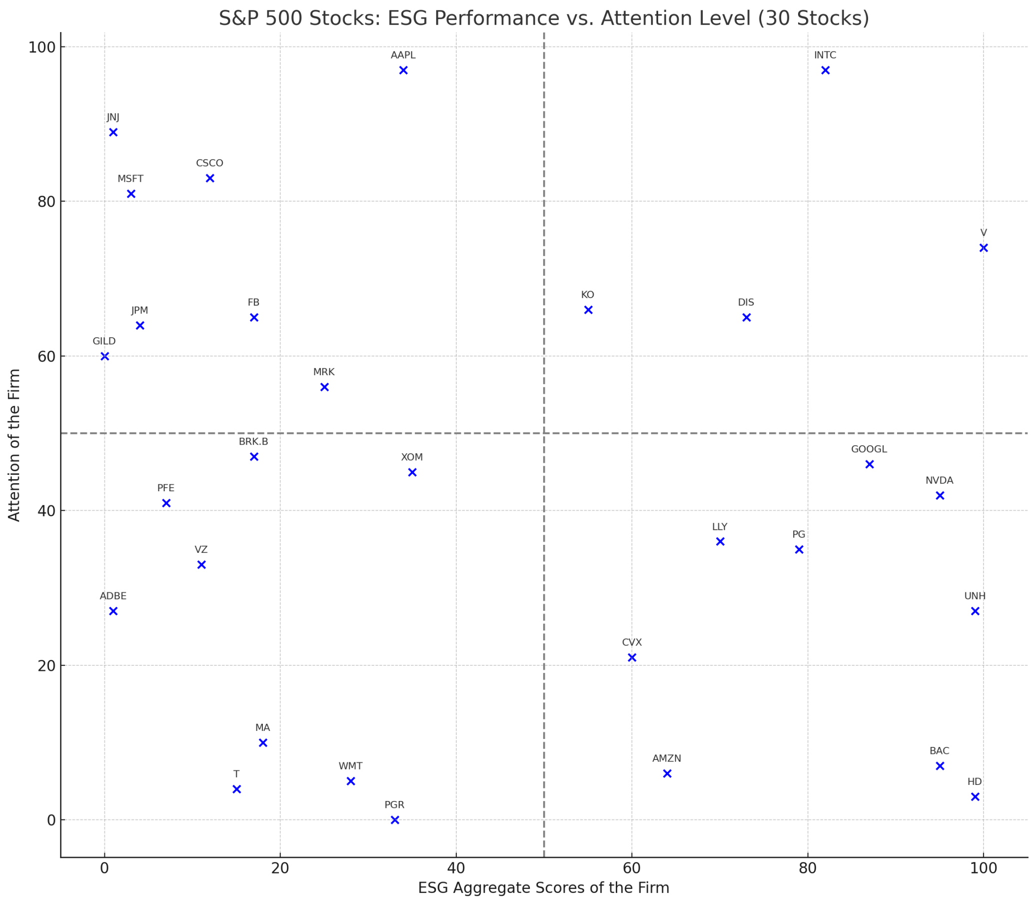

Figure 2: 30 Representative S&P 500 Stocks: ESG Performance vs. Attention Level

I begin with the setting of investors' heterogeneous beliefs about different states of the world, and they are trying to solve utility maximization problems from Campbell, 2018.

Consider a representative individual agent i in a two-period maximization problem regarding whether to buy a specific stock. The utility function $u(\cdot)$ is the utility function of an investor holding a specific stock and it is dependent on the investor's perception of the stock's performance in the environment, social, and governance space. In this hypothesized world, there are S potential states of the ESG profile changes, the investor i will allocate a portion of their wealth to establish a stock portfolio with positions $C_i(1), \cdots, C_i(S)$ such that $C_i(1) \leqslant C_i(2) \leqslant \cdots \leqslant C_i(S)$.

The agent i is endowed with a beginning wealth of W_{i0}. And the agent's total wealth at period 1 will depend on the stock value given the specific state realization $s \in S$ in period 1. The central two-period total utility maximization problem is thus formulated as the following, where C_{i0} is the wealth used on stock positions in period 1, and β is the discount factor for the utility to hold stocks in the second period.

$$\max u(C_{i0}) + \sum_{s=1}^{S} \beta \pi_i(s) u(C_i(s)) \tag{8}$$

subject to

$$C_{i0} + \sum_{s=1}^{S} q(s) C_i(s) = W_{i0} \tag{9}$$

I assume that the utility of an investor to hold a specific stock portfolio is equal to the sum of the utility to hold each stock. Thus, it suffices to look at agent i's decision for each stock under different states and just get the first order conditions and derive the first order conditions:

$$\beta \pi_i(s) u'(C_i(s)) = q(s) u'(C_{i0}), s = 1, \cdots, S \tag{10}$$

$$q(s) = \frac{\beta \pi_i(s) u'(C_i(s))}{u'(C_{i0})} \tag{11}$$

and the state price $q(s)$ turns out to be a dependent function of the investor's gauge of the underlying probability of the states, which represents whether the ESG ratings of the stocks held by the investors will improve or decline.

In the model, the agent i can choose a combination of only one high-attention stock and one low-attention stock with the same fundamental cash flow statements and return rates in period 0.

For simplicity, assume that there are only three disjoint states $S = \{P, U, N\}$ that can occur in period 1 for each stock. From period 0 to period 1, state P represents that the ESG profiles of the stock improve, state N represents that the ESG profile of the stock declines, and state U represents that the the ESG profile of the stock remains unchanged.

Such beliefs in the probability depend on the degree of attention the agent i pays to individual stocks. I denote the agent i's belief probability that the high-attention stock will experience a positive, neutral, or negative shift in ESG performance to be respectively $\pi_i(P,H), \pi_i(U,H), \pi_i(N,H)$. Similarly, let $\pi_i(P,L), \pi_i(U,L), \pi_i(N,L)$ be the probability that the low-attention stock will experience a positive, neutral, or negative shift in ESG performance. For the low-attention stock, the agent i's view on the stock's ESG performance will be less likely to reflect the actual change, and thus π_U will be higher. Consequently, agent i's perceived probability for π_P and π_N will be lower for low-attention stocks.

Assume the share of investment on the high-attention stocks in period 0 is α $(0 < \alpha < 1)$ and the share of investment on the low-attention stocks in period 0 is $1 - \alpha$. Given no cash option is permitted here (which is a fair assumption because retail investors tend to manage an independent stock portfolio aside from their checking or savings account), the agent i invests $\alpha(W_{i0} - C_{i0})$ in the high-attention stock in period 1 and $(1-\alpha)(W_{i0} - C_{i0})$ in the low-attention stock. $C_i(P,H)$ is the consumption that can be financed by returns from investment in the high-attention stock in period 1 if state P gets realized, and similarly, $C_i(N,L)$ is the consumption that can be financed by returns from investment in the low-attention stock in period 1 when state N is realized.

$$\begin{aligned}
\max \quad & u(C_{i0}) + \beta\Big\{\pi_i(P,H)u[C_i(P,H)] + \pi_i(U,H)u[C_i(U,H)] \\
& + \pi_i(N,H)u[C_i(N,H)] + \pi_i(P,L)u[C_i(P,L)] \\
& + \pi_i(U,L)u[C_i(U,L)] + \pi_i(N,L)u[C_i(N,L)]\Big\}
\end{aligned}$$

Plug in the consumption in period 1 by the investment returns that will finance them respectively, the objective function is:

$$
\begin{aligned}
\max \quad & u(C_{i0}) + \beta \Big\{ \pi_i(P,H) u\left[(1+r_H) I_i(H)\right] + \pi_i(U,H) u\left[(1+r_H) I_i(H)\right] \\
& + \pi_i(N,H) u\left[(1+r_H) I_i(H)\right] + \pi_i(P,L) u\left[(1+r_L) I_i(L)\right] \\
& + \pi_i(U,L) u\left[(1+r_L) I_i(L)\right] + \pi_i(N,L) u\left[(1+r_L) I_i(L)\right] \Big\}
\end{aligned}
$$

subject to the following budget constraint where W_{i0} is the initial endowment, and $I_i(H)$ and $I_i(L)$ are respectively the investments into the high-attention stock in period 1. r_H and r_L are the return rates from the high-attention stock and the low-attention stock.

$$
I_i(H) = \alpha(W_{i0} - C_{i0}), I_i(L) = (1-\alpha)(W_{i0} - C_{i0}) \tag{12}
$$

and probability belief differences due to attention differences:

$$
\pi_i(P,H) > \pi_i(P,L), \pi_i(U,H) < \pi_i(U,L), \pi_i(N,H) > \pi_i(N,L) \tag{13}
$$

Model 1B: two-periods model with a high-attention stock, a low-attention stock, and cash.

As an extension, I include the cash now into the setup of model 1. The agent i now has an option of earning risk-free interest r_f from period 0 to period 1. Let the share of the cash in his investment portfolio be γ, then the stock will be $(1-\gamma)$. Thus, the investment in high-attention stock will be $(1-\gamma)\alpha$ and $(1-\gamma)\alpha$ in high-attention stock of the total unused wealth in period 0.

$$
\begin{aligned}
\max \quad & u(C_{i0}) + \beta \Big\{ \pi_i(P,H) u\left[(1+r_H) I_i(H)\right] + \pi_i(U,H) u\left[(1+r_H) I_i(H)\right] + \\
& \pi_i(N,H) u\left[(1+r_H) I_i(H)\right] + \pi_i(P,L) u\left[(1+r_L) I_i(L)\right] + \\
& \pi_i(U,L) u\left[(1+r_L) I_i(L)\right] + \pi_i(N,L) u\left[(1+r_L) I_i(L)\right] \Big\} + \\
& u\left[(1+r_f)\gamma(W_{i0} - C_{i0})\right]
\end{aligned}
$$

Subject to the following budget constraint:

$$
I_i(H) = (1-\gamma)\alpha(W_{i0} - C_{i0}), I_i(L) = (1-\gamma)(1-\alpha)(W_{i0} - C_{i0}) \tag{14}
$$

and probability belief differences due to attention differences:

$$
\pi_i(P,H) > \pi_i(P,L), \pi_i(U,H) < \pi_i(U,L), \pi_i(N,H) > \pi_i(N,L) \tag{15}
$$

After taking first-order conditions and reorganizing the terms, I find the core result from model 1A and model 1B to be the following:

Agent i, with limited attention, in general, would set $I_i(H) > I_i^*(H)$, which is the optimal amount that agent i should have invested in to maximize expected utility. And $I_i(L) < I_i^*(L)$. However, this does necessarily indicate that $I_i(H) > I_i(L)$ for representative agent i. I am only suggesting that because the share α in the risky stock, among both stocks, is set lower than optimal α^*.

This is very intuitive based on the relationship between ex-ante expected returns r_H and r_L. I assume that investors would prefer to hold stocks with higher ESG performance if other factors are held constant because Higher ESG performance stocks provide better climate hedges Pástor et al., 2021 and Holding such stocks makes the investor feel good. If state probability $\pi_i(P,H) > \pi_i(N,H), \pi_i(P,L) > \pi_i(N,L)$, then one should expect $r_H < r_L$, because the alpha opportunity from positive change in the ESG performance of the stock is more priced in for the higher attention stock. Thus, $r_H < r_L$ is the more general pattern. [10]

Since individual retail investors are usually less informed and have fewer capabilities to maintain comprehensive market coverage, they naturally end up not being able to extract what has not been priced in by the market.

Additionally, if this model needs to be generated to an infinite-periods model with a high-attention stock, a low-attention stock, and cash, it suffices just to use dynamic programming technique to transform it into the two-period optimization problem with a separate budget constraint for every period and its next period, which reduces to Model 1b.

Model Implications

This simple theoretical model points to the importance of retail investor sentiments on their associated investment behaviors if they are ESG-aware. This paper's empirical findings of the sentiment lag patterns and the theoretical model gives rise to the following hypotheses that are intuitively appealing and present opportunities for future finance research to explore empirically.

First, the sentiment lag should be lower, and return predictability should be higher for the companies with lower attention (cognitively sticky, for example, you always consider the entire energy sector to be very gray). Since investors' aggregate sensitivity to adjust their perceptions on changes in such stocks' ESG profiles is lower, the correlation between future ESG sentiments with prior ESG sentiments is a lot higher as well. Second, following Lewellen, 2002's explanation that autocorrelation explains momentum returns without time series predictability, in stock returns, we should expect to document a more obvious momentum of ESG factor for low-attention stocks. Third, there should be more excess return opportunities in low attention and large ESG change stocks due to the aggregate biases of retail investors with attention constraints.

[10] I can verify this empirically by showing that stocks with higher attention, as proxied by coverage in financial news, tend to have lower returns. Despite this, it is hard to control for two stocks that have precisely the same profile with different attention.

8 Conclusion

This paper shows that the public can perceive the changes in the ESG space of the corporate world, but it happens with a lag. It takes the public approximately one or two quarters on average to process the information on public companies and change their sentiments or attitudes. The change in sentiments, however, does not necessarily align well with the objective changes as evaluated by reliable third-party rating agencies. While corporate managers care about Environment, Social, and Governance, their efforts and actual performances do not always satisfy the public. I show that improvements in the environmental metrics of a company do not significantly predict a positive shift in public sentiments, whereas improvements in social and governance metrics drive the public sentiments better. After taking out the time and industry invariant characteristics, the environment, social, and governance variables from one quarter ago or two quarters ago are consistently significant across the timeframe of the panel from 2010 to 2021 in this paper. They are more significant than the contemporaneous environment, social, and governance variables and have better predictability of public sentiments. I take the first step to explain the salience of ESG in affecting public sentiments that are not financial statement related, relative to many alternative theories.

This paper's empirical finding that companies' improvements the ESG performance do not necessarily correlate with better public ESG sentiments reveals some important concerns about sustainable investing. The public tends to be averse to holding stocks in the traditionally less green sectors, and this means that the firms in those sectors making big improvements are not rewarded for their ESG efforts. If private equity firms invest in traditionally 'brown' firms that are substantially improving their ESG performance, that should look like a reward that encourages positive transitions. However, private equity firms also face disclosure pressure from the limited partners (like university endowments) who fund them and face pressure and demands from the public, so they may be reluctant to invest in those companies. The natural question that arises behind this is admonishing our society: if the large firms making good endeavors to transition to a more sustainable future are not recognized for their efforts, would they gradually choose to commit fewer resources to those endeavors just like those worst continuous polluting firms at large? This poses a challenge to ESG investing as well: facing reputation concerns, investment management firms face a tradeoff between catering to the potentially biased public sentiments on certain sectors (such as energy or manufacturing) and investing in firms making the most positive ESG commitments and changes. In this respect, this paper takes a first step and points out the need for future research to solve this dilemma.

This paper believes that the subtle relationship reflects the fact that the public has more knowledge and a sense of engagement when they look at corporate social agendas but lacks the necessary knowledge and attention on corporate environmental affairs. The inattention of the public, among which many are retail investors, holds subjective, sticky views that adjust slowly. When it comes to making investment decisions, I establish this simple canonical model that shows that inattention could lead to mistakes in sustainable portfolio decisions due to false estimations of state probabilities, if the investor is aware of ESG regardless of the investor's flavor.

This may provide an interesting perspective for a source of investors' bias in securities pricing. The specific asset pricing implications of the attention lag in incorporating the changing ESG views can be modeled by testing the inclusion of a public sentiment factor against the benchmark portfolio.

Intuitively, there may be more excess return opportunities in low-attention and large-ESG-change stocks. The natural questions for future research are to investigate how the sentiment lag pattern and retail investor misinformation affect return predictability using multiple metrics, such as return on assets, price equity ratios (Campbell and Shiller, 1988 and Cochrane, 2008), or simply adjusted stock returns. In broader terms, this paper documents the pattern in the sentiment changes following changes in ESG profiles. Hopefully, If the public sentiments could reflect the changes more accurately, they would be a much better motivation for public companies to do their duties to safeguard against environmental risks and damages, promote responsible corporate governance, and contribute to build a more sustainable future for our society. We have seen that this is not yet true, which leaves questions for researchers, regulators, investors, and the general public.

9 Appendix

1. Summary Statistics on Key Variables: Twitter Sentiments, Sustainalytics Environment, Social, and Governance Ratings, Ravenpack Attention Scores

Table 1: Summary Statistics

Variable Series	Count	Mean	SD	1-percentile	50-percentile	99-percentile
Sentiment score	8312	20.8	35.6	0.3	17.8	76.3
Environment score	16577	55.6	13.2	32.6	54.2	86.2
Social score	16577	56.6	10.7	35.0	56.0	82.8
Governance score	16577	64.4	8.6	45.3	64.5	84.0
Stock return	22846	0.04	0.17	-0.36	0.04	0.49
Attention score	17949	9212	108788	42	398	121360

Environment, social, and governance scores are on the scale of 0 to 100, whereas sentiment scores and attention scores are extracted from textual sources and not normalized so that the actual magnitudes are reflected. Additionally, since ESG is a relatively new topic to talk about online it is computationally intensive to construct public sentiments from Twitter. Thus, the panel of this paper runs from 2010Q1 up to 2021Q4, which includes 48 periods in total. I didn't include tweets of 2022 and 2023, because I made the panel stop in 2021 before Elon Musk acquired Twitter and changed its name to X for several reasons. First, Musk also temporarily limited the number of tweets users could read, which makes the user sentiments revealed from the tweets less reflective of their actual attitudes and attention. Second, since 2022, Musk has made massive cuts to the content moderation team, which makes Twitter more susceptible to misinformation and more extreme, divisive views that deviate from the actual public sentiments. And most importantly, Elon Musk shut down the API access to scrape tweets. Thus, for the sake of data quality and accuracy, I stopped the panel in 2021.

2. Fuzzy Match Techniques

I fuzzy match the S&P 500 firms covered in Ravenpack Equities 4.0 Database to their corresponding tickers following the Jaro–Winkler distance from Jaro, 1989 and Levenshtein distance from Levenshtein, 1965. I finally choose to use Jaro-Winkler distance as it works better in the setting of financial media, as opposed to other distance measures widely available. Jaro-Winkler distance is also more generally used in economics and management papers for fuzzy matching. To ensure complete accuracy, I manually check the accuracy of all the matches. See online code appendix for more details.

3. Empirical Results Tables

Table 2: Regression 1-4 of Sentiments Without Filling in Missing Values.
This table reports regressions 1-4 of the quarterly unimputed environment, social, governance, proxied attention ratings, and their one-quarter-lagged and two-quarters-lagged versions on public sentiments of S&P 500 firms. It also indicates which fixed effects each regression includes. T-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is respectively indicated by ***, **, and *.

Variable	Regression 1	Regression 2	Regression 3	Regression 4
Environment	-0.01	-1.30	-0.44^{***}	-0.28
	(0.06)	(0.71)	(0.13)	(0.14)
Social	-0.17^{*}	-1.32^{**}	-0.40^{**}	-0.34^{*}
	(0.08)	(0.50)	(0.15)	(0.16)
Governance	-0.02	0.65	0.21	-0.20
	(0.09)	(0.54)	(0.16)	(0.19)
Attention	No			
Lag(Environment)	No			
Lag(Social)	No			
Lag(Governance)	No			
Lag(Lag(Environment))	No			
Lag(Lag(Social))	No			
Lag(Lag(Governance))	No			
Lag(Attention)	No			
Firm FE	No	No	Yes	Yes
Industry FE	No	Yes	No	No
Time (Quarter) FE	No	No	No	Yes
Industry*Quarter FE	No	No	No	Yes
R^2	0.00	0.07	0.01	0.15
Adjusted R^2	0.00	0.01	-0.15	-0.05
Observations	3540	201	3540	3540

Table 3: Regression 5-9 of Sentiments Without Filling in Missing Values.
This table reports regression 5-9 of the quarterly unimputed environment, social, governance, proxied attention ratings, and their one-quarter-lagged and two-quarters-lagged versions on public sentiments of S&P 500 firms. The table indicates which fixed effects each regression includes. T-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is respectively indicated by ***, **, and *.

Variable	**Regression 5**	**Regression 6**	**Regression 7**	**Regression 8**	**Regression 9**
Environment	0.12	0.02	0.02	−0.12	0.02
	(0.25)	(0.25)	(0.31)	(0.31)	(0.31)
Social	−0.65*	−0.58*	−0.61	−0.75*	−0.61
	(0.26)	(0.26)	(0.32)	(0.30)	(0.32)
Governance	0.00	−0.08	−0.20	0.41	−0.20
	(0.33)	(0.33)	(0.40)	(0.37)	(0.40)
Attention	No	No	0.00	−0.00	−0.00
	No	No	(0.00)	(0.00)	(0.00)
Lag(Environment)	−0.48	0.20	0.19	−0.55	−0.48
	(0.25)	(0.35)	(0.42)	(0.31)	(0.25)
Lag(Social)	0.39	−0.09	−0.12	0.35	0.39
	(0.26)	(0.35)	(0.43)	(0.30)	(0.26)
Lag(Governance)	−0.26	0.15	0.17	−0.23	−0.26
	(0.32)	(0.45)	(0.54)	(0.36)	(0.32)
Lag(Lag(Environment))	No	−0.71**	−0.88**	No	−0.87**
	No	(0.25)	(0.30)	No	(0.31)
Lag(Lag(Social))	No	0.52*	0.65*	No	0.64*
	No	(0.26)	(0.31)	No	(0.31)
Lag(Lag(Governance))	No	−0.41	−0.50	No	−0.49
	No	(0.32)	(0.38)	No	(0.39)
Lag(Attention)	No	No	No	0.00	−0.00
	No	No	No	(0.00)	(0.00)
Firm FE	Yes	Yes	Yes	Yes	Yes

Table 3 Continued from previous page

Variable	**Regression 5**	**Regression 6**	**Regression 7**	**Regression 8**	**Regression 9**
Industry FE	No	No	No	No	No
Time (Quarter) FE	Yes	Yes	Yes	Yes	Yes
Industry*Quarter FE	Yes	Yes	Yes	No	Yes
R^2	0.15	0.15	0.22	0.01	0.22
Adjusted R^2	−0.05	−0.05	0.03	−0.14	0.03
Observations	3519	3496	2854	2866	2847

Table 4: Regression 1-4 of Sentiments with Missing Values Imputed.

This table reports the results of regressions 1-4 on the quarterly imputed environment, social, governance (ESG) profiles, and proxied attention ratings, along with their one-quarter-lagged and two-quarters-lagged versions, against the public sentiments of S&P 500 firms. It details the fixed effects included in each regression. T-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Variable	**Regression 1**	**Regression 2**	**Regression 3**	**Regression 4**
Environment	−0.02	−0.10	−0.07***	−0.06**
	(0.02)	(0.05)	(0.02)	(0.02)
Social	−0.01	0.02	−0.01	−0.03
	(0.03)	(0.08)	(0.02)	(0.02)
Governance	−0.03	0.19	0.04*	0.02
	(0.03)	(0.10)	(0.02)	(0.02)
Attention		No		
Lag(Environment)		No		
Lag(Social)		No		
Lag(Governance)		No		
Lag(Lag(Environment))		No		
Lag(Lag(Social))		No		
Lag(Lag(Governance))		No		
Lag(Attention)		No		
Firm FE	No	No	Yes	Yes
Industry FE	No	Yes	No	No
Time (Quarter) FE	No	No	No	Yes
Industry*Quarter FE	No	No	No	Yes
R^2	0.00	0.02	0.00	0.05
Adjusted R^2	0.00	−0.01	−0.02	0.01
Observations	22896	528	22896	22896

Table 5: Regression 5-9 of Sentiments with Missing Values Imputed.

This table reports regression 5-9 of the quarterly imputed environment, social, governance, proxied attention ratings, and their one-quarter-lagged and two-quarters-lagged versions on public sentiments of S&P 500 firms. The table indicates which fixed effects each regression includes. T-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is respectively indicated by ***, **, and *.

Variable	**Regression 5**	**Regression 6**	**Regression 7**	**Regression 8**	**Regression 9**
Environment	0.02	0.01	0.02	−0.03	0.02
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
Social	−0.08	−0.07	−0.09	−0.10*	−0.09
	(0.04)	(0.04)	(0.06)	(0.05)	(0.06)
Governance	0.04	0.04	0.04	0.10	0.04
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
Attention	No	No	0.00	−0.00	0.00
	No	No	(0.00)	(0.00)	(0.00)
Lag(Environment)	−0.09*	−0.05	−0.06	−0.06	−0.06
	(0.04)	(0.05)	(0.07)	(0.04)	(0.07)
Lag(Social)	0.06	−0.02	−0.02	0.09	−0.02
	(0.04)	(0.06)	(0.08)	(0.05)	(0.08)
Lag(Governance)	−0.02	0.01	0.01	−0.05	0.01
	(0.05)	(0.07)	(0.09)	(0.05)	(0.09)
Lag(Lag(Environment))	No	−0.04	−0.06	No	−0.06
	No	(0.04)	(0.05)	No	(0.05)
Lag(Lag(Social))	No	0.08	0.09	No	0.09
	No	(0.04)	(0.05)	No	(0.05)
Lag(Lag(Governance))	No	−0.03	−0.03	No	−0.03
	No	(0.05)	(0.06)	No	(0.06)
Lag(Attention)	No	No	No	−0.00	0.00
	No	No	No	(0.00)	(0.00)
Firm FE	Yes	Yes	Yes	Yes	Yes

Table 5 Continued from previous page

Variable	**Regression 5**	**Regression 6**	**Regression 7**	**Regression 8**	**Regression 9**
Industry FE	No	No	No	No	No
Time (Quarter) FE	Yes	Yes	Yes	Yes	Yes
Industry*Quarter FE	Yes	Yes	Yes	No	Yes
R^2	0.05	0.05	0.07	0.00	0.07
Adjusted R^2	0.01	0.01	0.02	−0.02	0.02
Observations	22419	21942	18032	18424	18032

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