

Sentiment over Scores: Text-based ESG analytics for sustainable investment decisions

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Certificate of Original Authorship

I, Ellenora Webster, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Business School at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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Abstract

Interest in environmental, social, and governance (ESG) investing is waning after more than a decade of phenomenal growth. Contributing to this decline are challenges associated with the definition and measurement of ESG. Traditional ESG ratings data, a central metric in ESG investing, have been criticised for being backward-looking, non-transparent, slow to update, and inconsistent between providers. The resulting confusion, stemming from the reliance on unreliable measures, leads to conflicting conclusions in empirical research, increases inefficiencies in financial markets, and undermines investor efforts to achieve sustainability goals.

In recent years, forward-looking, timely, and objective measures of ESG, such as ESG sentiment, have become available. This dissertation applies ESG sentiment to existing problems in sustainable finance and aims to answer the following question: “How can sentiment address limitations of traditional ESG ratings, and enhance our understanding of risk and return in financial markets”? This research is critical as it addresses the pressing need for more timely and accurate ESG metrics to guide and restore faith in sustainable finance.

This dissertation begins by summarising the issues relating to traditional measures of ESG in Chapter 2. Importantly, it introduces the ESG sentiment dataset used in our analysis and discovers an exciting deviation from the expected properties of sentiment data when contrasted with stylised facts of sentiment. In Chapter 3 we explore the relationship between ESG uncertainty and stock price volatility. We find that ESG sentiment indicators are valuable predictors of stock price volatility, however it reveals that not all sentiment are created equal. Finally, Chapter 4 investigates the “equity greenium” puzzle and introduces a novel metric, “Breaking Buzz!” that transforms sentiment to be comparable with traditional ratings. Crucially, this chapter reveals that delays in ESG classification can significantly influence the equity greenium.

My work demonstrates that ESG sentiment can serve as a dynamic and effective alternative to traditional ESG ratings. By analysing ESG sentiment data, this research highlights key informa-

tional differences from traditional ratings, and yields interesting insights into ESG characteristics as it relates to stock price volatility and the equity greenium puzzle. With the introduction of innovative metrics such as Breaking Buzz!, this research offers practical tools for investors and policymakers to integrate ESG sentiment into their analysis and investment decision-making. Finally, these findings underscore the potential of dynamic-ESG to transform risk modelling and asset pricing, offering practical solutions to sustainable investing in a rapidly evolving financial landscape.

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Chapter 1

Introduction

Investor preferences for sustainable investment are having a profound effect on markets. The effect is such that recent work by Pástor et al. (2021) and Pedersen et al. (2021) suggests that equilibrium models, which have traditionally been the cornerstone of finance theory, may now be incomplete without considering environmental, social, and governance (ESG) factors. To quantify the global impact of sustainable investment, 4,827 investors managing US\$128.4 trillion in assets under management (AUM) have signed up to the United Nations Principles of Responsible Investment (UN PRI) as of March 2024.¹

However, since 2022, ESG has faced intense scrutiny and investor backlash.² One contributing factor to the backlash is the challenge of defining and measuring ESG. ESG ratings data (Traditional ESG), a measurement central to assessing a company's sustainability characteristics, have been criticised for being non-transparent, backward-looking, and slow to update. Moreover, inconsistencies in ESG performance measurements between ratings providers cause confusion for investors, leading to conflicting conclusions in empirical research, impacts asset pricing, and undermines investor efforts to achieve sustainability goals (see Chatterji et al., 2016; Berg et al., 2022).

Advances in Artificial Intelligence (AI) technology, such as Natural Language Processing (NLP), have enabled the development of forward-looking, timely, and objective measures of ESG, such as ESG sentiment, which present an alternative to traditional ESG performance measures.

¹UN PRI 2024 Annual Report, accessed 27-Jan-2025. <https://www.unpri.org/about-us/about-the-pri/annual-report>.

²See Washington, P., Jones, A. (2023) "ESG backlash is real and growing: What to know", Barrons, 21 September, accessed 27 January 2025 <https://www.conference-board.org/publications/barrons-ESG-backlash-is-real-and-growing>

Utilising this data, this dissertation aims to answer the following question: “How can sentiment address limitations of traditional ESG ratings, and enhance our understanding of risk and return in financial markets”. Crucially, this thesis challenges preconceived notions of ESG investing and reveals differences in outcomes when decomposing ESG performance into their respective E, S and G pillars. Moreover, it highlights that the source of sentiment, whether it originates from news or social media, can have a significant impact on results. This research is critical as it addresses the pressing need for increased transparency and timeliness of existing ESG measures to guide and restore faith in sustainable finance.

This chapter provides an overview of the main focus of each subsequent thesis chapter, outlining the modelling approaches and main results. It also discusses how this work fits with the literature and highlights its contribution.

1.1 Chapter 2: Beyond traditional ESG: Unlocking the power of news and social media for ESG investing

Investors use Environmental, Social, and Governance (ESG) ratings (Traditional ESG) to evaluate a company’s sustainability credentials and its exposure to financially material physical and transition risks associated with ESG concerns. However, the quality and value of ESG ratings have become the subject of fierce criticism among researchers and practitioners. This criticism arises due to inconsistencies among rating providers, the slow update frequency of the data, and the reliance on a company’s self-reported disclosures and documents (see Chatterji et al., 2016; Brandon et al., 2021; Berg et al., 2022; Serafeim and Yoon, 2022), leading investors to discard ratings as provided and compile their own from raw datasets (Brock et al., 2023). Concerns related to the quality of ESG ratings can be categorised into two domains: 1) conceptualisation of what ESG means and how it should be measured, and 2) data and procedural considerations. Developments in Artificial Intelligence (AI) and data collection techniques aim to address issues categorised under the latter domain, such as improved timeliness of data and increased objectivity, and have resulted in an availability of rich datasets for researchers to examine alternative ways to consider ESG performance.

This chapter examines a type of alternative ESG measure, ESG sentiment from Refinitiv Marketpsych ESG Analytics (RMEA), and performs a comprehensive review to assess its useful-

ness for ESG research. Specifically it investigates the insights that sentiment provides regarding ESG trends, whether ESG sentiment measures are consistent with stylised facts of sentiment, and whether ESG sentiment possesses predictive power for common market variables, before answering the question: How does ESG sentiment contrast with traditional ESG scores?

Our analysis yields several interesting insights. Focusing on 50 salient companies within the United States, we find a clear preference in the communication channels used by investors when discussing ESG topics. Moreover, when we examine attention to the varying ESG topics, we observe distinct preferences across industry groups providing a first insight to materiality from a public perspective. Additionally we find an interesting deviation in the environmental pillar from the behaviour expected from stylised facts of sentiment. Finally, we confirm informational differences between the sentiment measure of ESG performance and a traditional measure. This last point is critical for any future analysis to justify the use of an alternative measure of ESG beyond what has traditionally been used.

This research contributes to the ESG data debate by focusing on the role of public opinion in forming novel ESG measures. Our findings reveal that sentiment can add a different dimension to our understanding of ESG and offers a guide to future researchers, investors, and policy makers wanting to integrate sentiment into their analysis.

1.2 Chapter 3: ESG sentiment and stock market volatility

This chapter follows on from the previous by applying sentiment and attention variables from the RMEA database to investigate the impact that ESG sentiment has on stock price volatility. In particular, it examines whether uncertainty in ESG contributes to risk. This analysis is pertinent considering that ESG considerations are increasingly normalised in investment decisions. Understanding volatility dynamics following discussion around ESG events or changes in sentiment regarding a company's ESG activities is crucial for financial institutions and asset managers, especially in relation to risk management and modelling ESG-integrated portfolios over time.

In this study, we investigate both the explanatory and predictive power of ESG sentiment and attention measures on volatility, and aim to answer the following three questions: 1) Does uncertainty in ESG contribute to an increase in stock price volatility; 2) which data source has the greatest impact on volatility; 3) which ESG pillar affects volatility the most? To answer these questions, we follow the framework of Audrino et al. (2020) in utilising the heterogeneous autoregressive (HAR) model, an extension of the classic HAR model of Corsi (2009), to include

sentiment, attention and economic variables in an ESG setting.

In Panel-HAR regressions, we find strong evidence that ESG-related media activity influences volatility, driven by media attention and dispersion in ESG sentiment. When decomposing sentiment by media source, individual regressions reveal that social media is better at explaining and predicting volatility. Similarly, we find the social pillar to be better than the environmental and governance pillars when decomposing into pillar groups. Interestingly, despite the literature that advocates the separation of ESG into pillar groups for analysis, we find our results are strongest when a composite measure of ESG incorporating sentiment from all media sources are used.

This study leverages several key features of the dataset. High-frequency sentiment and attention measures at 1-minute intervals allow for optimal aggregation and analysis, and is crucial for maximising sentiment's predictive power. The dataset also separates sentiment from news and social media, enabling independent analysis of these information sources. Finally, the dataset decomposes sentiment into environmental, social, and governance (E, S, and G) pillars, allowing for detailed analysis of their individual impacts on volatility. These findings have important implications for risk managers and answers an important question as to whether ESG factors should be considered in risk models. This chapter extends the work of Audrino et al. (2020) by decomposing sentiment into environmental, social and governance pillars, and contributes to the literature on ESG risk.

1.3 Chapter 4: Breaking Buzz! Extracting materiality from media

Economic theory and equilibrium models posit that agents with a preference for sustainability should anticipate lower expected returns, as green firms benefit from a lower cost of capital (El Ghouli et al., 2011; Seltzer et al., 2022), or are perceived to be less risky (Chan et al., 2020; Hoepner et al., 2024). Yet, when testing this empirically, the opposite is found to be true, resulting in a positive equity premium when subtracting the realised returns of a brown portfolio from a green portfolio (GMB) (Pástor et al., 2022). The discrepancy between expected and realised return is frequently attributed to an increased preference for sustainable assets, which drives asset prices higher due to demand-induced price pressure (Brandon et al., 2020; Pástor et al., 2021, 2022; Ardia et al., 2023). This chapter challenges the conventional explanation and

proposes that the observed positive equity premium from the GMB factor may be due in part, to a delay in classifying stocks as green or brown.

We introduce a novel metric: “Breaking Buzz!” which captures the timeliness and materiality in sentiment, and transforms sentiment into a measure that is comparable with traditional ESG. We formulate GMB portfolios in the spirit of Pástor et al. (2021, 2022), using both traditional ESG and Breaking Buzz! measures to sort stocks into green and brown portfolios. We find no evidence of an equity greenium in the GMB portfolio formulated from the Breaking Buzz! measure suggesting that the frequency with which the ESG performance measure is updated can materially affect the equity greenium.

Our results underscore the limitations of traditional ESG metrics in capturing real-time sustainability performance and highlights their potential to distort portfolio dynamics. The introduction of the Breaking Buzz! metric contributes to the ongoing discourse relating to ESG measurement and offers a practical solution for investors and policymakers to integrate ESG sentiment into financial-decision making.

1.4 Contribution

This thesis intersects three main strands of literature: ESG, investor sentiment, and volatility modelling. This section summarises the contributions this thesis makes to the related literature. Detailed comparisons of each chapter with related papers are presented within the corresponding chapter.

A substantive debate persists in the literature regarding the relevance of ESG factors as determinants of risk and return in financial markets. Despite the extensive literature, definitive conclusions remain elusive. We add to the discussion on whether ESG contributes to risk by investigating the impact of ESG sentiment on stock price volatility in Chapter 3. Crucially, we provide an alternative interpretation of ESG uncertainty that differs from the existing literature (see Brandon et al., 2021; Avramov et al., 2022), and establish a link between disagreement in public discourse and an increase in stock price volatility. Separately, this research contributes to the literature that examines the relationship of sentiment with stock price volatility (Antweiler and Frank, 2004; Caporin and Poli, 2017; Audrino et al., 2020). We modify the sentiment-HAR model proposed by Audrino et al. (2020) to include ESG sentiment. In Chapter 4 we contribute to the greenium debate (Pástor et al., 2021, 2022) by providing an alternative explanation to the positive equity greenium reported by Pástor et al. (2022).

We also make substantial contributions to the discourse regarding ESG data. At its inception, ESG ratings were heralded as a way to link ESG concerns with investment decisions, providing a means to standardise conceptualisations of sustainability (Eccles et al., 2020). However, several shortcomings of ESG ratings data have recently come to light. We add to this stream of literature in the following ways. First, by demonstrating the impact that a delay in classification can have on portfolio dynamics in Chapter 4, we add to the discussion critical of traditional ESG ratings (see Chatterji et al., 2016; Berg et al., 2022). Second, by utilising ESG sentiment data in our analysis, we add to the growing body of research employing alternative datasets to investigate the impact of ESG (Serafeim, 2020; Taleb et al., 2020; Hughes et al., 2021; Teodoro et al., 2023). We further advance this literature by introducing the concept of using sentiment as a proxy for ESG performance, and providing the mechanism through which to do so using our novel Breaking Buzz! metric. Third, we contribute to the literature dissecting information yielded by pillar groups (Malshe et al., 2023) by revealing that insights obtained in one pillar group cannot be assumed for the others.

Finally, our use of ESG sentiment contributes literature that investigates the role of sentiment on market dynamics. In their seminal paper, Baker and Wurgler (2007) advance studies into the effects of sentiment on stock prices with the creation of a sentiment index. Since then, advancements in textual analysis, computing power, and data storage capacity mean that richer signals of sentiment are now available and at higher frequencies (refer to Antweiler and Frank, 2004; Tetlock, 2007; Da et al., 2014, for an evolution in sentiment analysis). Moreover, the nature of information has changed: where information used to be viewed through the lens of corporate press releases and news wires, the advent of social media has changed the notion of information transmission (Gan et al., 2020) and its effect on financial markets (Ranco et al., 2015; Sun et al., 2016). The novelty of this thesis lies in decomposing sentiment into distinct groups of discussion (environmental, social, or governance) and analysing their individual impact on financial markets. Furthermore, by dissecting sentiment into its news and social media sources, we join a growing body of research that contrasts sentiment by media source (see Gan et al., 2019).

Chapter 2

Beyond traditional ESG:

Unlocking the power of news and social media for ESG investing

2.1 Introduction

Investors use Environmental, Social, and Governance (ESG) ratings to evaluate a company's ESG performance or to assess the risk of exposure from financially material physical and transition risks associated with ESG concerns. However, the quality and value of ESG ratings have become the subject of fierce debate among researchers and practitioners due to inconsistencies among rating providers, the low frequencies with which the ratings are available, and dependence on a company's self-reported disclosures and documents, and have led to increasing scepticism about their usefulness (see Chatterji et al., [2016](#); Brandon et al., [2021](#); Berg et al., [2022](#); Serafeim and Yoon, [2022](#)).

Given the shortcomings of current ESG measurement methods, this paper explores sentiment analysis as an alternative metric for assessing ESG performance. We begin by discussing how a sentiment-based measure can overcome some of the challenges associated with traditional ESG metrics. This is achieved in three ways. First, being independent of corporate influence and focusing exclusively on public opinion. Second, by limiting points of subjectivity in performance

assessment. Finally, the availability of a performance measure in real-time.¹

Given the differences between ESG sentiment and traditional ESG, a key question arises: how do ESG sentiment-based scores compare statistically and economically with traditional ESG scores or other qualitative methods for assessing ESG impact? Before addressing this question however, it is essential to first understand the characteristics of ESG-based sentiment measures. To this end, we conduct a comprehensive review of the ESG-sentiment-based measures to investigate the following questions: 1) what insights does sentiment provide regarding ESG trends? 2) are ESG sentiment measures consistent with stylised facts of sentiment; and 3) does ESG sentiment possess predictive power for common market variables? Finally, we compare our ESG sentiment measure against a common traditional measure and test the hypothesis that ESG sentiment possesses the same informational value as traditional measures.

We obtain the ESG-sentiment measures from Refinitiv Marketpsych ESG Analytics (RMEA), a novel, commercial database providing sentiment-based measures of ESG performance obtained strictly from news and social media sources. One of its key advantages is the provision of data at high frequencies allowing for dynamic evaluation of ESG performance. Although databases of a similar nature have previously found applications in the literature, such as the ESG sentiment measures provided by TruValue Labs (Serafeim, 2020; Taleb et al., 2020), it is still a new area of research.

Our review begins with a global examination of the RMEA dataset to gauge the level of media focus on ESG, referred to as “*Buzz*” and the resulting sentiment, “*Sent*”, across news and social media platforms. Three observations emerge. First, there is a pronounced disparity in ESG discussion between Developed (DM) and Emerging (EM) markets. This discrepancy may be driven by several factors such as a greater focus on ESG in developed markets, media accessibility, language biases, or classification bias. Notably, the United States surpasses all other countries in terms of both media attention and coverage, providing a compelling reason to concentrate our analysis on the United States for the remainder of this paper. Second, ESG discussions were more prevalent in news media than social media, a trend observed in both DM and EM countries. This finding is intriguing, considering social media’s perceived democratising influence and the expectation of higher media activity on these platforms. Third, ESG-related media coverage has increased over time, with sentiment becoming more positive. The trend towards positive

¹We emphasise a crucial distinction between the philosophical foundations underpinning the formulation of the ESG measure and those based on data or procedural considerations. We contend that alternative ESG measures can only tackle issues related to the latter while resolving the former requires policy settings or a universal consensus.

sentiment is especially prominent in news media for the Environmental and Social pillars in both Developed and Emerging markets. This finding draws parallels with observations by Daugaard and Ding (2022) who find that generally, ESG ratings tend to improve over time.

Next, we focus on the United States and contrast the ESG sentiment-based measures from news and social media on 50 of the most salient companies. Salient companies are defined as companies that are prominent in people’s minds, either due to their size, economic presence, or investor attention. As sentiment data is notoriously sparse, analysis of salient companies also ensures sufficient data is available for meaningful analysis. In this section, we introduce the concept of using sentiment as a measure of materiality and examine the trend of ESG sentiment over time. Additionally, we test sentiment-based variables against two well-established stylised facts of sentiment: 1) Media activity around earnings announcements, and 2) Performance around extreme information events.

Our analysis of salient companies yields several interesting insights. First, there is a clear preference for the communication channels used by investors in the discussion of ESG topics for companies belonging to certain industries. For instance, companies within the Financial industry group and the Industrials industry group are more likely to be discussed in news media, whilst Technology companies feature more prominently in social media. We also observe preferences in the discussion of ESG topics vary across industry groups and media platforms, providing a first insight into materiality from a public perspective. We also observe that ESG sentiment trends positively over time, and that news media displays a strong positive bias. Testing the hypothesis that sentiment regardless of where it is derived should satisfy stylised facts of sentiment, we find a deviation from expected behaviours for environmental topics in social media only.

The contrast in saliency between the two media types prompts an investigation into the informational content arising from ESG discussions in news and social media. To examine this, we focus on a single stock, Apple Inc. due to its prominence in the public domain, and examine the time-series characteristics of the sentiment variables, *Buzz* and *Sent*. We also investigate their predictive power by performing cross-correlations up to ± 20 lags against three key market variables: stock returns, trading volume, and realised volatility. We find a significant contemporaneous correlation between *Sent* and stock returns in both news and social media with correlations of 0.13 and 0.17 respectively. For both the *Buzz* and *Sent* variables, there appears to be a persistence in the relationships between volume and realised volatility for social media, whilst in news media *Buzz* appears to be a significant predictor of realised volatility.

Finally, we contrast our measures of ESG performance with a traditional benchmark - MSCI

ESG ratings. MSCI ESG ratings are used widely across academia and industry and are generally considered to be the largest provider of ESG ratings (see Eccles et al., 2020; Berg et al., 2022; Pástor et al., 2022). For this reason, we consider MSCI to be a useful benchmark. In pairwise ranking t-tests we confirm that the ESG-sentiment measures are statistically different from traditional measures of ESG, and also between media source. We then examine the time series evolution of the alternate and traditional ESG measures on four representative stocks from different sectors: Apple Inc. (Information Technology), Pfizer Inc. (Health Care), Walmart Inc. (Consumer Staples), and Exxon Mobile Corp. (Energy). We find ESG measures constructed from public opinion appear to lead the traditional ESG score, although causality was not established. Given the different frequencies of the datasets, it is plausible that a company’s activities surrounding its management of ESG risks and sustainability are reflected in the news and social media long before ESG rating scores.

This study contributes to the growing body of research on alternative ESG datasets by introducing a novel dimension of company-independent ESG data exploration using ESG-sentiment as a basis for the analysis. Moreover, it emphasises the role of public opinion in shaping ESG measures. Importantly, we extend the literature on the impact of company-related ESG news to include sentiment derived from social media and analysing their impact on asset prices. Finally, we present practitioners with a methodology with which to compute an ESG score, and contrast this with a traditional measure of ESG performance.

This chapter proceeds as follows: Section 2.2 provides the background and motivation for this paper, Section 2.3 describes the data and data processing techniques, Section 2.4 presents insights on ESG sentiment including global trends and stylised facts, Section 2.5 compares the sentiment measure with traditional measures of ESG performance, and Section 2.6 concludes.

2.2 Literature review

The growth in sustainable investment is perhaps the most dramatic trend to take place in the investment industry this decade. For example, the latest report by the Global Sustainable Investment Alliance (GSIA) in 2023 revealed that the AUM committed sustainable investing had grown from US13.6 trillion to US30.3 trillion between 2012 and 2022 (Global Sustainable Investment Alliance, 2022). Underpinning this growth is not only a desire for investments to align with investor values but also a recognition that an effective way to enforce change is through capital markets (Pástor et al., 2021; Pedersen et al., 2021). Far from being a one-off trend, sustainable

investing is now entrenched in the investor psyche. This results in a fundamental and enduring shift in the investment landscape, thereby reflecting a growing awareness of the long-term risks and opportunities associated with sustainable business practices, and ultimately reshaping the criteria by which investors assess the value and viability of their investment portfolios.

Central to sustainable investing are the data that form the foundation of the decision-making process. ESG ratings providers, such as those mentioned by Kotsantonis and Serafeim (2019) and Berg et al. (2022), collect extensive data from diverse sources, such as company disclosure documents, questionnaires, NGO reports, and increasingly, alternative data sources such as news and social media. These data are then combined with expert opinion to provide a quantitative measure of a company’s environmental, social, or governance (ESG) performance, which we refer to as traditional ESG. Traditional ESG can be thought of as the first generation of measures that attempt to quantify a company’s progress in meeting socially responsible goals and were born out of the first set of sustainability principles presented in a 2004 UN Global Compact report titled “Who cares wins”. This report was the first to link environmental, social and governance issues with investment decisions. The principles outline practices to advance responsible corporate citizenship in response to globalisation in the following areas: Human Rights, Labour, Environment, and Anti-Corruption. From these first principles, ESG measures have now evolved into huge datasets containing hundreds of data points.

Initially, traditional ESG was heralded as “the” solution to link environmental, social, and governance concerns with investment decisions. It gained praise for its simplicity, offering, for the first time a means through which the ESG performance of companies, industries, and even investment products, could be easily compared (Eccles et al., 2020). However, in recent years, as the complexities of measuring ESG performance became apparent, such as bridging philosophical differences in determining what ESG measures and how it should be measured, traditional ESG are now coming under enormous scrutiny.

Since the seminal work of Chatterji et al. (2016), the shortcomings of traditional ESG have been, and continue to be, extensively discussed in the literature, and highlight the deficiencies inherent within the conventional framework. These deficiencies, for example, highlight the challenges arising from the supply and quality of data required, divergent theorisations as to what the ESG ratings should measure, as well as variations in the methodologies used. Additionally due to differing uses of the ESG ratings by varying stakeholders and commercial interests of ratings providers, conflicts of interest may influence the quality of ESG ratings. We refer the reader to Berg et al. (2022) and Larcker et al. (2022) for a comprehensive overview of the predomi-

nant issues, and Brock et al. (2023) for a detailed industry assessment of the ratings landscape throughout 2023.

This discourse posits that the identified issues can be broadly categorised into two main domains: those intrinsic to the formulation of an ESG measure, such as disparities in interpretation or philosophical underpinnings, and those contingent on data or procedural considerations. The former encapsulates issues universally applicable to all providers, datasets, and measures. As such, resolution of this category of issues necessitates the standardisation of definitions, measurements, and methodologies, or a re-characterisation of measurements² across the ESG landscape. Conversely, issues falling within the latter category, we contend, may be mitigated through the use of alternative datasets and/or Artificial Intelligence (see also Hughes et al., 2021, for a summary of how AI can be used to address these issues). It could be argued that ESG data, being extra-financial, is in and of itself alternative data (In et al., 2019). For the sake of clarity, we define alternative ESG data as any ESG measurement that is sourced externally from the company and ideally, independent of company input. We outline four issues that fall into this latter category.

First, traditional ESG depend heavily on the information provided by the company when formulating an assessment on their ESG performance. Yet unlike financial disclosures, ESG disclosures are not yet standardised, affording companies discretion in what they report and how they choose to report it (Amel-Zadeh and Serafeim, 2018; Kotsantonis and Serafeim, 2019; Berg et al., 2022). The opportunity for self-reporting means that the data feeding into the ratings represents a sanitised version, or at worst, greenwashing (Yu et al., 2020; De Silva Lokuwaduge and De Silva, 2022) of a company’s ESG activities, painting the company in a more positive light than may be deserved.

Second, the reliance on company disclosures and reports also affects the currency of the assessment being provided of a company’s ESG performance, and how relevant that may be for investors who are forward-looking by nature. Whilst company disclosures and reports provide a historical account of the company’s activities and ESG performance, they are inherently backward-looking, thereby affecting the currency of the assessment being provided. Third, the low frequencies with which company disclosures and reports are made available mean that ESG ratings are limited to these lower frequencies (typically annually). In essence, these latter points illustrate the limitations of traditional measures of ESG performance in providing investors with a

²For example we agree with the proposal advocated by Eccles et al. (2020) for ratings to be characterised into one of two groups: value-based (measuring a company’s impact to society), or values-based (measuring impact to financial performance).

timely perspective of a company’s ESG performance and therefore, their usefulness in predicting future ESG performance.

Finally, human analysts analyse the information once the data is collected and determine the company’s ESG profile. Whilst this provides the benefit of combining data with expert opinion, it also allows for a high degree of subjectivity to be embedded throughout the whole process. This results in assessments that may be inconsistent from one analyst to another or even throughout time.

2.2.1 An alternative measure – ESG sentiment

With the rapid development of Artificial Intelligence (AI) techniques such as Natural Language Processing (NLP) and Machine Learning (ML) in recent years, practitioners and researchers have turned towards alternative data sources and methods to address some of the shortcomings described in the previous section relating to data and processes. For example, satellite imagery, news articles, social media, and job postings have all been used to identify new sources of ESG activity (or risk) for a company (In et al., 2019; Dor et al., 2022; Hansen and Borch, 2022). Researchers are also drawing their attention to the informational content that ESG news can provide (Capelle-Blancard and Petit, 2019; Cui and Docherty, 2020; Serafeim, 2020; Taleb et al., 2020).

While only few studies investigate the role of ESG news, their main findings include: the higher frequencies with which ESG news is available is complimentary to the trend of investors taking a dynamic view of ESG investing (Taleb et al., 2020); results are mixed on reactions to news with Capelle-Blancard and Petit (2019) and Cui and Docherty (2020) finding evidence of larger negative price reactions to negative news, whilst Serafeim (2020) finds 75bp spread in reaction between positive and negative news for company’s conditioned on low ESG performance; finally, disagreement in ESG performance hampers the timely incorporation of information in prices (Serafeim and Yoon, 2022).

More recently, studies are turning to text mining and other text-based analysis to study the impact of ESG sentiment (Dorfleitner and Zhang, 2024; Zhou et al., 2024). For example, Dorfleitner and Zhang (2024) builds an ESG dataset based on raw ESG news by applying the BERT model on unstructured data. In this study they find the impact of news varies depending on a company’s historical record. Meanwhile, Zhou et al. (2024) utilises the Baidu Sentiment Tendency Analysis model to depict the text characteristics of ESG disclosure for Chinese A-Share listed banks. Interestingly, they find higher media attention and negative sentiment lowers the

readability of bank ESG disclosure text.

We focus on one specific type of alternative data, namely ESG sentiment derived strictly from news and social media sources using the latest text-based analysis and NLP techniques. We highlight the key benefits of using this type of data, specifically focusing on a commercial database provided by Refinitiv Marketpsych ESG Analytics (RMEA) and discuss how they may address the shortcomings outlined in the previous section.

An obvious difference between a sentiment-based measure and a traditional score is the much higher frequency with which the sentiment measure can be updated. Automated textual analysis techniques that extract information from credible news and social media sites allow for real-time analysis of E, S and G activities and whether the activity is positive or negative for the company. The RMEA database for example is able to provide observations as granular as at 1-min frequencies, thus contrasting with traditional ESG measures which are typically updated only annually. Whether this results in a meaningful signal that is useful to investors or just simply noise is an open question that we leave for future research.

An important distinction between RMEA and traditional ESG ratings is that the NLP engines avoid articles or references to a company's own (self-reported) documents, press releases and filings. This external perspective of a company's sustainability characteristics and the frequency with which the scores can be generated have notable benefits for investors. Firstly, external perspective avoids the potential for a company to greenwash or mislead investors regarding the company's sustainability efforts (Szabo and Webster, 2019). However, not all statements released by companies are representative of their true environmental position and many companies have been called out by critics and environmental groups for making misleading claims that are contradictory to their actions.³ Incorporation of company announcements and news releases, therefore, may bias the company's ESG rating as companies are incentivised to present themselves positively. Second, it goes some way to addressing the size bias inherent in the way traditional ESG scores are constructed where the positive correlation between higher ESG performance and company size has been linked to resources available to address requests for information on ESG performance (Drempetic et al., 2020).

Given these distinctions, an obvious question arises: how do ESG sentiment-based scores compare statistically and economically with traditional ESG scores or other qualitative methods

³In one example a complaint was filed against BP in 2019 for a misleading advertising campaign promoting its commitment to a low carbon future, despite 96% of its expenditure being on oil and gas. Laville, S (2019) "Lawyers lodge complaint over BP's 'misleading' ad campaign", 4 December, accessed 8 June 2022 <https://www.theguardian.com/business/2019/dec/04/activists-call-for-bp-adverts-to-carry-climate-damage-warning>.

for assessing ESG impact? To address this question, it is imperative first to understand the characteristics of ESG sentiment. In this context, we aim to explore the following questions: 1) what insights does sentiment provide regarding ESG trends? 2) are ESG sentiment measures consistent with stylised facts of sentiment? and 3) does ESG sentiment possess predictive power for common market variables? Finally, to rigorously compare ESG sentiment with traditional measures, we propose testing the hypothesis that ESG sentiment possesses the same informational value as traditional measures.

2.3 Data

2.3.1 Refinitiv MarketPsych ESG Analytics (RMEA)

Central to our analysis is the sentiment data obtained from Refinitiv MarketPsych ESG Analytics (RMEA). The RMEA database, publicly accessible since February 2021⁴, offers a novel dataset that captures public opinion on Environmental, Social, and Governance (ESG) themes in real-time from news and social media sources. This feature enables the database to serve as a dynamic proxy for ESG performance. Powered by MarketPsych Data’s advanced natural language processing (NLP) engine, the AI-driven ESG feed encompasses over 30,000 companies across 252 countries, with historical data extending back to 1998. In the United States, which boasts the most extensive news and social media coverage, the dataset includes 6,527 active and inactive public and private companies.

The RMEA database provides different types of scores that capture sentiment and media attention. RMEA computes these scores from two different content types: News and Social Media. The news content is sourced from over 4,000 credible news sites, and supplemented with selected sources from the LexisNexis aggregated news feeds. The social media content is sourced from over 2,000 distinct social media sources, obtained from MarketPsych’s and LexisNexis’s social media feeds. The combined content from news and social media means that in total, more than 2 million articles and posts are fed into the NLP engine daily to construct the RMEA scores.

Content is screened and classified according to perspective and outlook. Content creators who have the characteristics of ideologues, promoters, robots or spammers are removed from the feed both historically and in real-time. Importantly, RMEA excludes content generated by the company for which sentiment on sustainability is being assessed, such as the company’s own

⁴Finextra (2021) “Refinitiv rolls out MarketPsych ESG Analytics”, 17 February, accessed 20 February 2021 <https://www.finextra.com/pressarticle/86219/refinitiv-rolls-out-marketpsych-esg-analytics>.

reports, disclosures and press releases. This ensures a truly external perspective can be provided on a company’s ESG initiatives and performance that is untarnished by potential greenwashing by the company. Finally, to address English language bias in the sentiment scores, MarketPsych Data recently added Arabic, Chinese, Japanese and Portuguese-language sources in February 2020, and Dutch, French, German, Indonesian, Italian, Korean, Russian and Spanish-language sources in January 2021.

The engine analyses the contents of media articles and social media posts by mapping them to a specific entity and assigning one of over 4,000 ESG-related variables, known as *ESGVars*. These variables are generated by the engine and, although not directly visible to the user, include examples such as *AnimalTestingPerform*, *AntiTrustViolate*, *BenefitsCorpExpand*, and *Pollution-Heal*. In addition to this mapping, each *ESGVar* is further qualified by a “verb tense” indicator, which signifies whether the referenced action in the text relates to the past (*_p*), future (*_f*), or is conditional (*_c*). This qualification adds contextual clarity to the sentiment analysis by distinguishing between actions that have already occurred, are anticipated, or are hypothetical. Figure 2.1 presents an excerpt from Refinitiv (2020) to illustrate this process.

FIGURE 2.1: **Marketpsych ESG Score Construction.** Excerpt from Refinitiv (2020) of a sentence level example of the NLP engine analysing a sentence and prescribing a score.

Sentence-level Example

Using the principles outlined above, below is a closer look at the MarketPsych NLP software analyzing this sentence:

“Amazon is going to significantly lengthen paternity leave.”

The language analyzer performs the following sequence:

1. Maps the term “Amazon” to the company’s unique identifier (AI pattern-matching redirects geographic references to the river and region if appropriate).
2. Identifies “paternity leave” as a *BenefitsCorp* word in the lexicon.
3. Identifies “going to” as a future-oriented word and assigns future tense to the phrase.
4. Identifies “lengthen” as an *Expand* word.
5. Multiplies “lengthen” by 2 due to the presence of the modifier word “significantly.”
6. Associates “lengthen” (*Expand*) with “paternity leave” (*BenefitsCorp*) using dependency parsing.

The analysis algorithm will report:

Date	Time	assetCode	Ticker	ESGVar	Score
20200804	15:00:123	4295905494	AMZN	BenefitsCorpExpand_f	2

In the example above, 2 is the raw score produced for *BenefitsCorpExpand_f* attributed to Amazon.

A key concern for users of this dataset is the effect of changes to the NLP engine on sentiment estimates, particularly whether historical data are re-estimated following such updates. One risk is the introduction of temporal look-ahead bias, which may occur if the engine is trained on data containing information that overlaps with or predates the test period (Glasserman and Lin, 2023). Language itself evolves over time, and the social meaning of words can shift. For example, the word “woke” referenced in the mid-2010’s with a positive connotation to mean a person being awake to social issues, now is used pejoratively as push against progressive politics. This kind of semantic drift can complicate sentiment analysis across time, and lead sentiment measures to appear more negative (or positive) in earlier periods than was contextually appropriate.

2.3.2 RMEA variables

The RMEA database⁵ provides different types of sentiment and attention variables at two levels of granularity: *Category* and *RMA* scores. In total there are 111 variables, available at 1-minute, 1-hour, and daily frequencies, and as one of three content sets: News only, Social media only, or as News and Social media combined.

The most granular variables are the 80 sentiment-based *RMA* scores which capture sentiment on specific Environmental, Social or Governance Topics, such as *airborneEmissions*, *anger*, and *managementSentiment* for a given entity. Each *RMA* score is defined as being either an *ESG* or a *Controversy* score. The *ESG* score captures the positive and negative sentiment associated with a company’s ESG activities reported in the media. They are bi-polar in their construction, ranging between -1 and 1, and are positive in their tonality, meaning that a higher score is subjectively positive. *Controversy* scores on the other hand, capture sentiment relating to controversial activities, measuring only the prevalence of subjectively negative themes, events or emotions. Unlike their *ESG* counterpart, they are unipolar in their construction ranging between 0 and 1, and are negative in their tonality, implying that a high score is subjectively negative. It is important to note that by their construction, the underlying variables that contribute negatively to the *ESG* score may be present in the *Controversy* score, however, the reverse may not be true. Therefore, it is important to highlight that if the research question requires a single measure of sentiment, it would be prudent to merge these two scores.

The next level of aggregation are the *Category* scores which capture the sentiment from discussion on ESG topics associated with one of ten categories: *emissions*, *environmentalInnova-*

⁵Sentiment data from Refinitiv Marketpsych ESG Analytics is available in two packages: Core and Advanced. The variables detailed here are available in the Advanced package.

tion, *resourceUse*, *community*, *humanRights*, *product*, *workforce*, *management*, *shareholders*, and *csrStrategy*. They can be considered as aggregations of the 80 granular *RMA* and *Controversy* scores. Each category will represent references to a company’s commitment and effectiveness at obtaining a set of objectives within the category, or any discussion relating to key words associated with the category. For example, the *emissions* category will contain all references to a company’s commitment to reducing carbon emissions in environmental and operational processes. Table 2.1 presents the category definitions outlined by Refinitiv (2020). In total, there are 10 Category *ESG* scores, and 9 Category *Controversy* scores.⁶

Finally, in addition to the sentiment-based variables are 12 variables measuring the volume of media attention. 11 *Buzz* variables which capture the volume of ESG-specific discussion relating to a company and are available as a total across all topics discussed or at the *Category* level, and 1 *Mentions* variable which captures the number of times the company was mentioned in media discussion. *Buzz* represents the sum of entity-specific ESG-related words and phrases used in score computations and weighted such that higher levels of discussion in the media will have a greater impact on the score. In this sense, not only *Buzz* capture the volume of discussion on related ESG topics, but also its intensity. *Buzz* therefore, is a critical variable for us and is a relevant proxy for ESG media attention. Table A.1.1 in the Appendix presents a full list of variables available in the RMEA database.

2.3.3 Data Aggregation

This section outlines the data aggregation process to formulate daily environmental, social, and governance pillar scores, and the daily composite ESG score from the granular category scores provided at 1-minute intervals. There are several reasons why a researcher would want to do this. Quite often, a data provider will provide a measure, however, its construction may not align with the specific use case for the researcher. For example, adjustments that alter the meaning of the signal as is the case with industry-adjustment of traditional ESG measures, or measures including or omitting information sets that the researcher may or may not require. This analysis requires the daily sentiment measure to include observations that span the window 09:35 t to 09:25 $t+1$ (EST) which encompasses the trading day + overnight sentiment. The daily measure provided by RMEA spans 15:00 $t-1$ to 15:00 t (EST) and excludes sentiment observations at market close, a critical period of the trading day.

⁶As at the last date of access, 23 November, 2023, a *Controversy* score was not available for the *CSRStrategy* category.

TABLE 2.1: **RMEA category variables representations.** This table presents the definitions of each category as defined by Refinitiv (2020).

Category	Description
<i>emissions</i>	All category references to a company’s commitment and effectiveness towards reducing environmental emission in the production and operational processes as well as references to environmental emissions by the company
<i>environmentalInnovation</i>	A company’s reduction of environmental impact and the creation of new market opportunities through new green technologies and design as well as references to production of environmentally damaging chemicals and socially unsustainable activities
<i>resourceUse</i>	A company’s energy efficiency and supply chain sustainability as well as a company’s energy wastefulness and inefficiencies
<i>community</i>	The company’s commitment towards being a good citizen, protecting public health and respecting business ethics as well as public anger, corruption, and legal scandals associated with a company
<i>humanRights</i>	Efforts to support human rights as well as violations of human rights including child labor, labor exploitation, human rights violations, and sanction violations
<i>product</i>	A company’s capacity to produce quality goods and services honouring the customer’s health and safety, integrity and data privacy as well as violations of data privacy, product flaws, deceptive advertising, unethical research, and customer dissatisfaction
<i>workforce</i>	Job satisfaction, workplace safety, maintaining diversity and equal opportunities, and development opportunities for the company’s workforce as well as references to employee accidents, layoffs, labour disputes, bias, and declining or limited benefits at a company
<i>cSRStrategy</i>	A company’s sustainability reporting
<i>management</i>	A company’s commitment and effectiveness towards following best practice corporate governance principles as well as management scandals associated with a company
<i>shareholders</i>	A company’s effectiveness towards equal treatment of shareholders and the use of anti-takeover devices as well as shareholder and financial controversies at a company

The procedure we outline here is based upon the methodologies provided by Marketpsych (Refinitiv, 2020), however we modify to suit our research requirements, for example, not applying the industry adjustment. We emphasise the importance of tailoring the aggregation process to the researcher’s specific use case, and the steps taken here are simply one example of how the data can be aggregated.

We start by combining the category *ESG* and *Controversy* scores to provide a comprehensive evaluation of the overall category sentiment (c) for company (j), intraday 1-minute intervals (i),

and for media source (k). We sign *Controversy* to align with the direction of sentiment before averaging the two measures into a combined score. This approach differs from others that have been described in the literature for a related product, Thompson Reuters Asset 4, (for example Yang et al., 2024). We take this approach due to the construction of the *ESG* and *Controversy* scores. Some (but not all) of the underlying variables that contribute to the controversy score may also be included in the ESG score. By taking the average we can ensure that the negative exposure is also considered without the potential of double-counting underlying variables that contribute to both measures. For brevity, we suppress the company and media type subscripts:

$$Sent_{i,c} = \frac{1}{2}(-Controversy_{i,c} + ESG_{i,c}). \quad (2.1)$$

Our next step is to aggregate the intraday observations into a daily signal based on our desired window length. To do this, we follow the procedure provided by Marketpsych (Refinitiv, 2020). We define our window as the 23:50hr period from 09:35 on day $t - 1$ (τ_1) to 09:25 on day t (τ_2). We exclude the 5mins immediately following (preceding) market open to avoid the volatility impacts associated with the opening session.

$$Sent_{t,c} = \frac{\sum_{i=\tau_1}^{\tau_2} Sent_{i,c} \times Buzz_{i,c}}{\sum_{i=\tau_1}^{\tau_2} Buzz_{i,c}}, \quad (2.2)$$

$$Buzz_{t,c} = \sum_{i=\tau_1}^{\tau_2} Buzz_{i,c}, \quad (2.3)$$

To create the pillar and composite scores from the underlying category scores, an important consideration is how to weigh the contribution of each category to the final score. We deviate from the approach presented in the RMEA methodology in the cross-sectional aggregation of the category scores into E, S and G pillars and the composite score in two important ways. First, we do not make an industry adjustment for our scores. This ensures not only that the scores are directly comparable to our traditional proxy (i.e. the MSCI pillar scores and the ESG composite score derived from the pillar scores), but also it ensures that the sentiment generated for a company is not affected by the overall sentiment of the industry. Second, we rely on the data to determine the weights of how each category contributes to the pillar and composite scores. Traditional scores rely upon internal methodologies to determine the materiality of a category or sub-level score to the pillar / composite scores. The approach that we take, i.e. *Buzz*-weighted average of the sentiment scores, allows materiality to be determined by public opinion, which in

our view is much more transparent.

We compute the pillar and composite measures for *Sent* and *Buzz* as:

$$Sent_{P,t} = \sum_{c \in P} \omega_{c,t} \times Sent_{c,t}, \quad (2.4)$$

$$Buzz_{P,t} = \sum_{c \in P} Buzz_{c \in P,t}, \quad (2.5)$$

$$\omega_{c,t} = \frac{Buzz_{c,t}}{\sum_{c \in P} Buzz_{c,t}}, \quad (2.6)$$

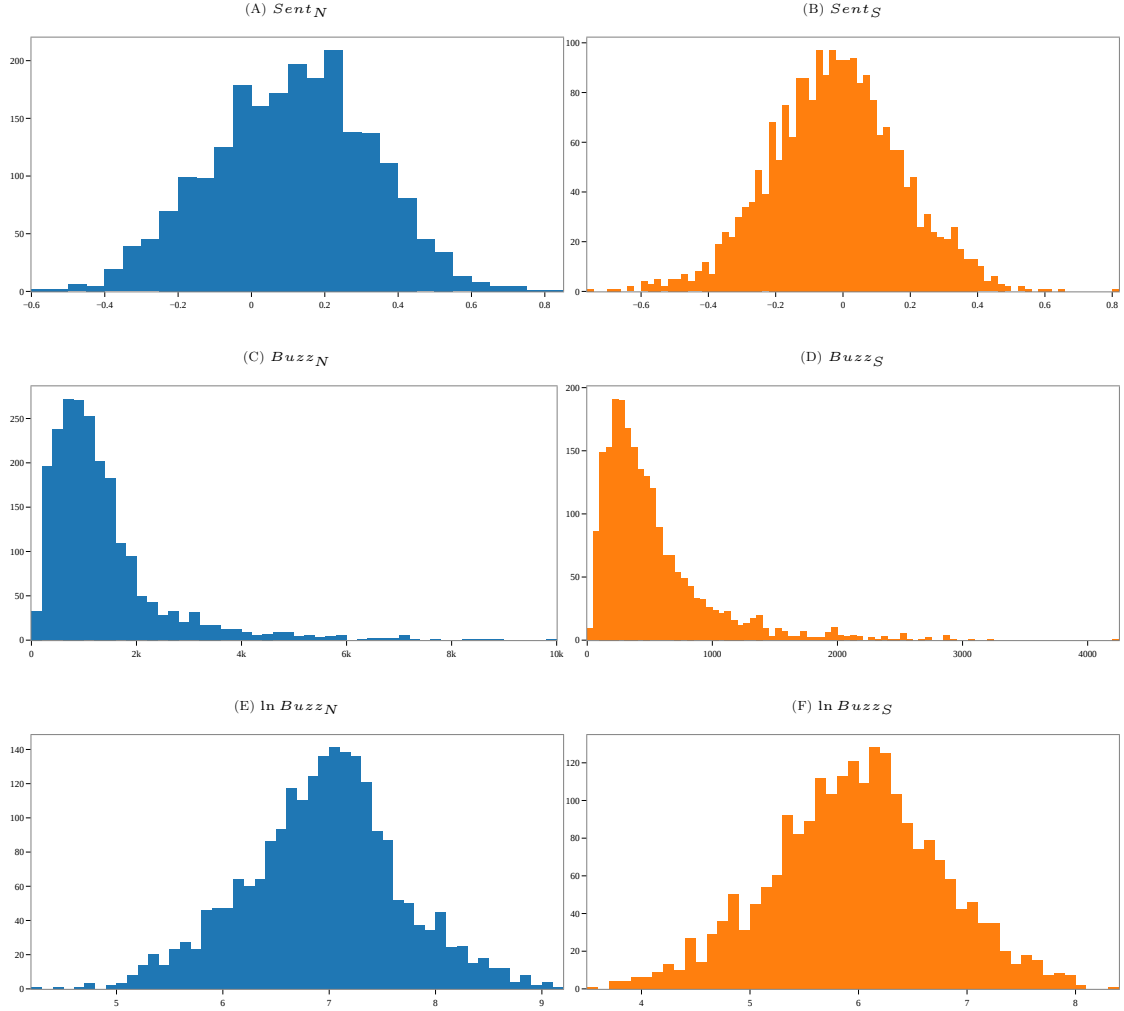
respectively, where P represents the environmental, social, and governance pillars or the ESG composite score.

To familiarise the reader with the properties of the aggregated series, we focus on the *ESG* composite *Buzz* and *Sent* scores for a single representative stock: Apple Inc. to plot its distributional and time series characteristics. Figure 2.2 plots the distribution of the *Sent* series (top panel), *Buzz* (middle panel), and $\ln Buzz$ (bottom panel) for news (LHS) and social media (RHS). It is easy to see that the *Buzz* series (Panels C and D) are not Gaussian displaying a strong positive skew with long and heavy tails. In Panels (E) and (F), we demonstrate how normality can be recovered in the *Buzz* series by applying a logarithmic transformation.

Figures 2.3 and 2.4 plot the aggregated score, autocorrelation functions (ACF) and partial-autocorrelation functions (PACF) up to 40 lags for *Buzz* and *Sent* respectively. We observe large outliers and weak weekly seasonality in the *Buzz* and *Sent* series for both news and social media.⁷ Winsorising the series will mitigate the effects of extreme outliers. We also observe strong persistence in the *Buzz* and *Sent* variables but for social media only. This is an interesting point of differentiation between the two media types. Since we assume the data-generating processes are the same we would expect some similarity in the time series characteristics between news and social media. This observation also contrasts with the same analysis conducted on a similar dataset by Gan et al. (2020) which showed strong persistence in the *Buzz* and *Sent* variables for both news and social media. On the surface, it does seem to suggest that in ESG-related discussion at least, that news media has a shorter memory than social media.

⁷The outliers present in *Sent* are likely to be the result of the data aggregation process since the underlying series are bounded by -1 and 1.

FIGURE 2.2: **Distribution of daily *Sent* and *Buzz* variables for Apple Inc.** This figure plots the histograms for *Sent* (top panel), *Buzz* (middle panel), and $\ln Buzz$ (bottom panel) for news (LHS) and social media (RHS). The daily *Sent* and *Buzz* series presented here are reconstructed from 1-minute observations following the data aggregation method outlined in Section 2.3.3. The sampling period is from 01-Jan-2016 to 31-Dec-2021.

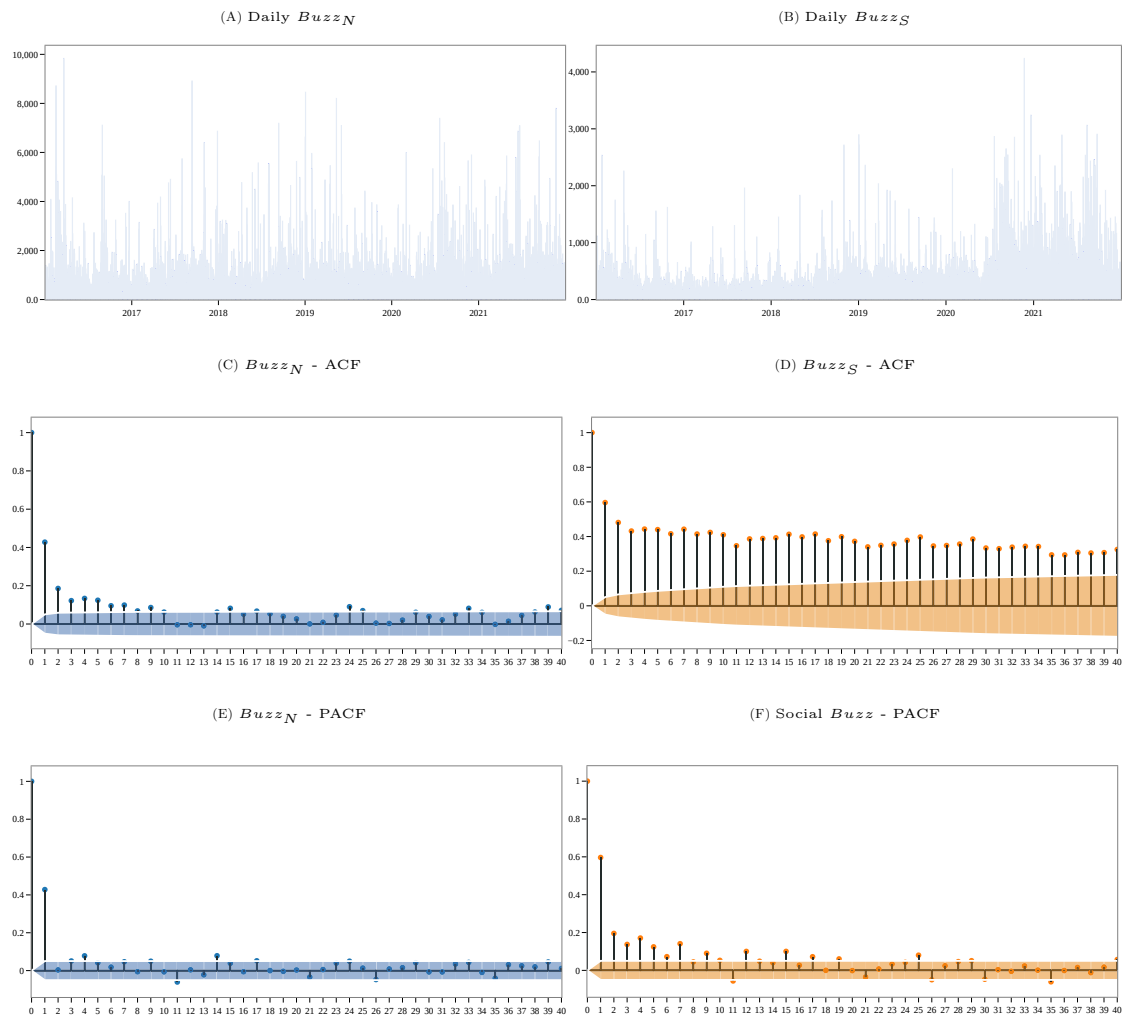


2.4 Insights

2.4.1 Global trends

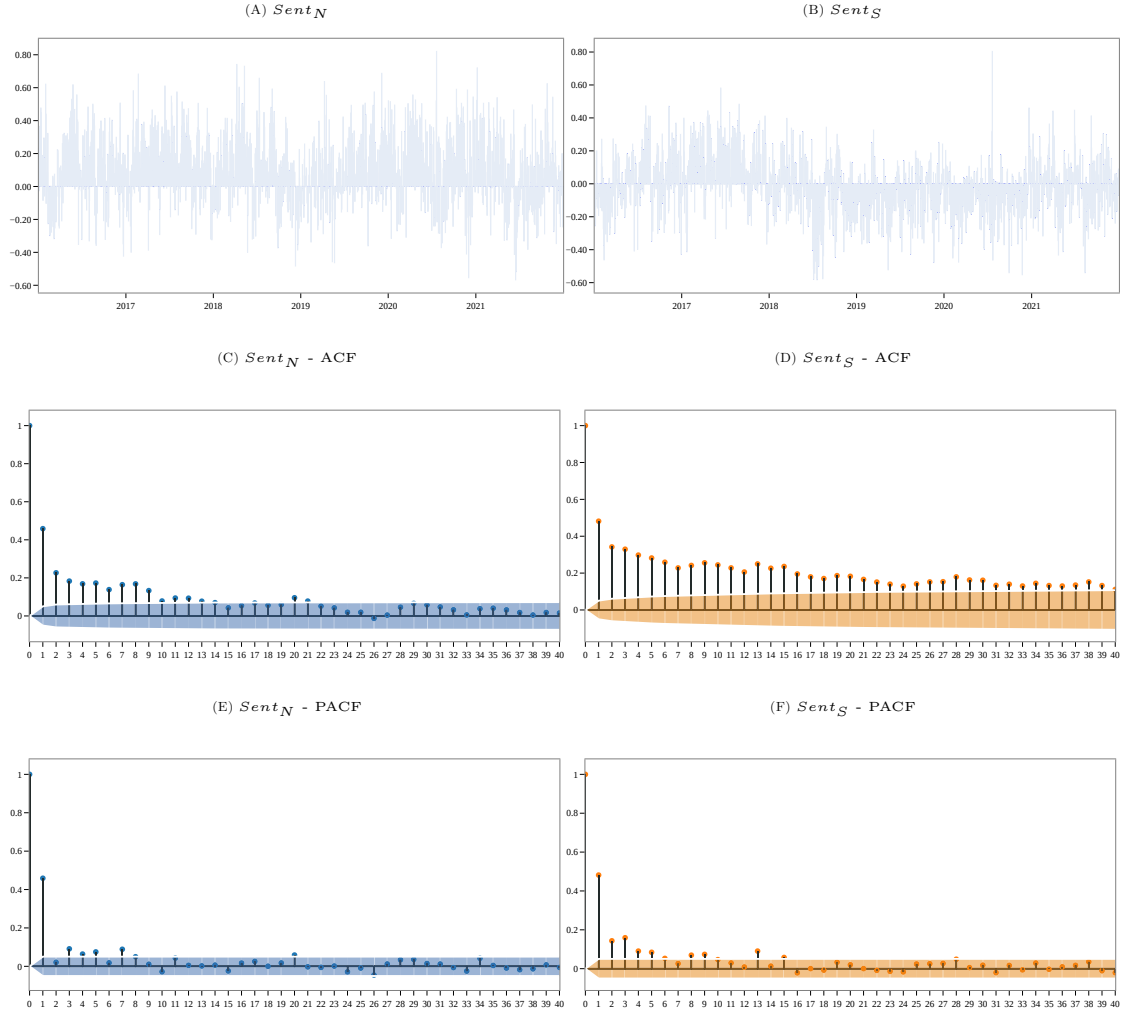
We start by performing a top-down exploration of the RMEA database to identify global interest and their trends in ESG. A growing consciousness for environmental sustainability and social justice means that increasingly, companies are facing intense scrutiny on their activities and ethical culture (Loughran et al., 2023). This is led in no small part by the trend towards

FIGURE 2.3: **Timeseries analysis of daily *Buzz* for Apple Inc.** The panels on the left hand side show the daily time series of *Buzz* derived from news media, its autocorrelation function (ACF) and partial-autocorrelation function (PACF). The panels on the right hand side show the same, but for social media. The daily *Buzz* series are reconstructed from 1-minute observations following the data aggregation method outlined in Section 2.3.3. The sampling period is from 01-Jan-2016 to 31-Dec-2021.



sustainable investing, where mechanisms, such as engagement and capital allocation, are used by investors to encourage firms to undertake sustainable and ethical business practices (Kölbel et al., 2020). Whilst much importance is placed on achieving sustainability goals in Developed markets such as in Europe or the United States, to what extent are these concerns replicated in the Global South? For example, when mapping sustainability patterns across the globe using the Sustainalytics ESG database, Daugaard and Ding (2022) finds a wide disparity between regions in meeting ESG aspirations that are underscored by the regulations and societal expectations in

FIGURE 2.4: **Timeseries analysis of daily *Sent* for Apple Inc.** The panels on the left hand side show the daily time series of *Sent* derived from news media, its autocorrelation function (ACF) and partial-autocorrelation function (PACF). The panels on the right hand side show the same, but for social media. The daily *Sent* series are reconstructed from 1-minute observations following the data aggregation method outlined in Section 2.3.3. The sampling period is from 01-Jan-2016 to 31-Dec-2021.



place within those regions. Do we see similar patterns and trends in public sentiment?

Table 2.2 summarises the global coverage of the RMEA dataset⁸ detailing the number of companies covered, level of ESG related media attention (Total *Buzz*), and average sentiment over the period between January 2007 and December 2022 for News and Social media (columns (1) to (3)), News media only (columns (4) to (6)), and Social media only (columns (7) to (9)). For

⁸For this section we obtain daily *Category* scores from the RMEA database and aggregate to pillar and composite scores per Eqns 2.4 and 2.5 in Section 2.3.3.

brevity, we report only the countries classified as Developed (DM) or Emerging (EM) economies by MSCI, with the final row showing the aggregated figures for the remaining countries (Rest of World).⁹

TABLE 2.2: **ESG media attention and sentiment of global markets.** This table presents the Refinitiv Marketpsych ESG Analytics (RMEA) database coverage of ESG discussion in global markets. Columns (1) to (3) present the number of companies covered, the total level of media attention (*Buzz*), and average sentiment *Sent* respectively, for each country generated from news and social media. Columns (4) to (6) present the same but for news media only, whilst columns (7) to (9) present for social media only. The countries listed are those classified as belonging to the MSCI Developed Markets or Emerging Markets indices as at April 2024, with the remaining countries aggregated under "Rest of World". Individual countries are sorted according to column (2). The sample period is from 01-Jan-2007 to 31-Dec-2022.

COUNTRY	All	All	All	News	News	News	Social	Social	Social
	# Companies (1)	Total Buzz (2)	Av Sentiment (3)	# Companies (4)	Total Buzz (5)	Av Sentiment (6)	# Companies (7)	Total Buzz (8)	Av Sentiment (9)
United States	6,227	178,949,514	0.0564	6,212	100,928,589	0.1160	6,166	78,020,925	0.0024
United Kingdom	821	17,370,356	0.0905	820	14,774,048	0.1007	804	2,596,309	0.0376
India	648	12,504,883	0.1028	648	8,981,133	0.0820	644	3,523,750	0.1091
Japan	1,125	11,386,345	0.1028	1,123	10,017,779	0.1101	1,008	1,368,566	0.0633
Germany	320	10,214,486	0.1123	320	9,041,923	0.1225	303	1,172,563	0.0757
China	2,498	9,946,474	0.0249	2,497	7,169,540	0.0318	2,131	2,776,934	0.0075
Canada	611	9,729,444	0.0857	611	5,990,734	0.1283	610	3,738,710	0.0226
Australia	983	6,931,875	0.0702	982	5,082,477	0.0831	978	1,849,399	0.0393
France	349	4,916,169	0.1153	349	4,264,486	0.1301	318	651,684	0.0608
South Korea	260	4,671,711	0.0933	259	3,973,849	0.0990	221	697,863	0.0652
Netherlands	141	4,533,171	0.1239	141	3,926,462	0.1367	132	606,710	0.0714
Switzerland	173	3,731,301	0.1003	173	2,994,634	0.1114	164	736,667	0.0477
Ireland	80	2,307,394	0.0607	80	1,421,050	0.0855	79	886,344	0.0191
Sweden	227	1,764,676	0.1370	227	1,582,102	0.1426	216	182,574	0.0835
Brazil	181	1,568,583	0.0190	181	1,392,168	0.0124	173	176,416	0.0146
Finland	54	1,548,653	0.1659	54	1,160,634	0.1804	52	388,019	0.0850
Spain	105	1,489,297	0.1123	105	1,374,262	0.1219	93	115,035	0.0473
South Africa	191	1,360,048	0.0383	191	1,225,757	0.0430	186	134,292	0.0112
Italy	184	1,278,965	0.0246	184	1,166,846	0.0280	158	112,120	-0.0033
Hong Kong	506	1,277,515	0.0352	506	1,074,262	0.0404	448	203,253	0.0097
Israel	150	1,150,904	0.0590	147	685,362	0.0869	141	465,542	0.0253
Denmark	70	1,104,556	0.1582	70	1,002,829	0.1656	69	101,727	0.1246
Singapore	175	1,050,904	0.0815	175	834,820	0.0906	168	216,084	0.0465
Taiwan	111	1,022,640	0.0656	111	736,648	0.0766	106	285,992	0.0389
Norway	144	946,260	0.1310	143	890,546	0.1397	134	55,715	0.0561
Philippines	53	643,757	0.1191	53	396,678	0.1445	53	247,079	0.0224
United Arab Emirates	46	619,048	0.1524	46	590,124	0.1527	46	28,925	0.0754
Malaysia	139	612,275	0.0683	139	478,444	0.0704	131	133,831	0.0330
Indonesia	114	467,440	0.0426	114	435,382	0.0428	96	32,058	0.0144
Thailand	183	457,012	0.0580	183	382,037	0.0717	180	74,975	0.0240
Greece	42	384,690	-0.0201	42	95,959	-0.0007	38	288,732	-0.0474
Belgium	62	310,228	0.0877	62	277,696	0.0935	58	32,532	0.0448
New Zealand	49	306,664	0.0943	49	267,818	0.0973	49	38,846	0.0531
Mexico	72	280,638	0.0388	72	235,714	0.0556	71	44,924	0.0077
Turkey	42	266,854	-0.0042	42	248,527	-0.0039	40	18,327	-0.0099
Saudi Arabia	58	198,424	0.0686	58	187,740	0.0657	57	10,684	0.0655
Poland	89	194,236	0.0107	89	167,422	0.0132	87	26,814	-0.0002
Austria	44	190,363	0.0562	44	178,249	0.0544	40	12,114	0.0324
Qatar	19	184,400	0.1371	19	171,619	0.1430	19	12,782	0.0134
Chile	92	133,616	0.0368	91	102,925	0.0597	83	30,691	0.0030
Egypt	17	92,417	0.0592	17	88,523	0.0580	17	3,894	0.0509
Portugal	19	88,180	0.0090	19	83,635	0.0021	15	4,545	0.0164
Kuwait	17	78,099	0.1171	17	76,559	0.1205	15	1,541	0.0370
Czech Republic	9	66,358	-0.0429	9	55,491	-0.0372	8	10,867	-0.0468
Colombia	9	36,387	-0.0199	9	32,418	-0.0538	9	3,969	0.0182
Peru	7	26,921	-0.0080	7	23,599	0.0060	6	3,322	-0.0262
Hungary	10	19,838	-0.0016	10	19,008	-0.0039	5	830	0.0258
Rest of World	659	4,783,105	0.0314	655	3,804,584	0.0372	594	978,521	0.0036

Companies were counted as being covered if they were mentioned at least once in a news or social media platform regardless of whether it relates to an E, S or G concern. This differs from the Total *Buzz* measure which captures the volume and intensity of discussion on an ESG topic and is calculated as the sum of daily *Buzz* values. Average sentiment is calculated as the mean

⁹We take a countries inclusion in the MSCI Developed Markets and MSCI Emerging Markets indices to determine which countries are classified as Developed and Emerging economies respectively (accessed 7 March 2024) <https://www.msci.com/our-solutions/indexes/>.

of daily sentiment. Countries are ranked according to Total *Buzz* generated from the combined media types.

It is clear that the United States dominates other countries covering 6,227 companies across news and social media platforms and receiving a Total *Buzz* of 178.9 million. These values are at least an order of magnitude greater than the next ranked country, United Kingdom, for which the database extracts sentiment from 821 companies with a Total *Buzz* of 17.3 million. India, ranked third, leads the emerging market economies covering 648 companies and generating *Buzz* of 12.5 million.

Comparing global coverage between news and social media, it is interesting to observe that more companies are mentioned in news media than for social media. Moreover, with the exception of Greece, the volume of ESG discussion is also greater in news media, and for some countries, significantly so. We find this observation somewhat contradictory to the findings of Gan et al. (2020) that supports social media being the dominant medium for information dissemination. It suggests that at least for discussion relating to environmental, social and governance topics, news media appears to be the preferred medium.

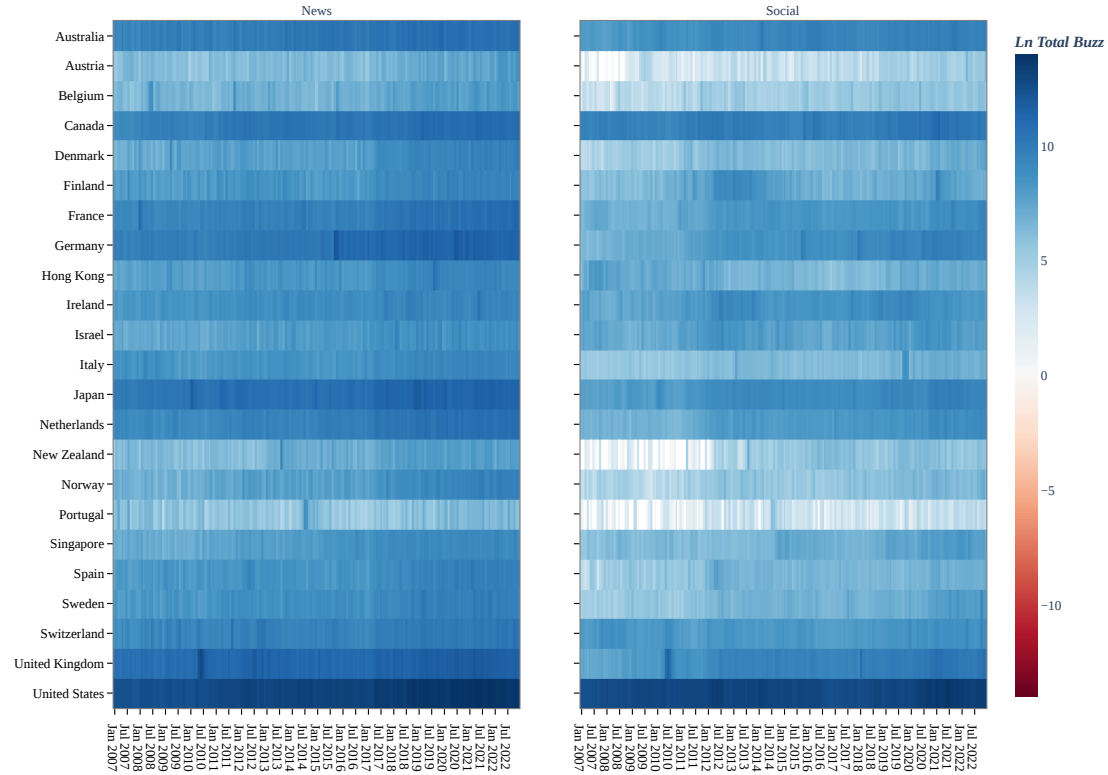
Table 2.2 also reflects a positive bias in average sentiment from both in news and social media for the majority of countries. We are again surprised by this observation given the asymmetric attention given to negative news (Tetlock, 2007), however find consistency with the notion that the sentiment is less positive in social media than for news media. The positive bias detected in the sentiment measure, might lead one to conclude that collectively companies globally are working to improve their sustainability footprint. However, how reliable is sentiment as an indicator of future progress towards sustainability? We leave this as a topic for future research.

We now look at the global trend of ESG discussion and sentiment. Figures 2.5 and 2.6 present total *Buzz* (or level of media attention) for each month-year between January 2007 and December 2022 for firms in developed and emerging markets respectively¹⁰ with discussion from news (social) media presented on the left (right) hand side. For ease of comparability, Total *Buzz* has been presented on a logarithmic scale.

It is clear that the level of ESG discussion in the media is increasing over time with the increase most prominent in social media for both the developed and emerging economies. Additionally, the dominance of news over social media detected in Table 2.2 appears to be consistent throughout the sample period for both the developed and emerging economies. The trend post 2016 presents

¹⁰countries are categorised as Developed or Emerging economies based on their inclusion on the MSCI DM or EM indices as of January 2024

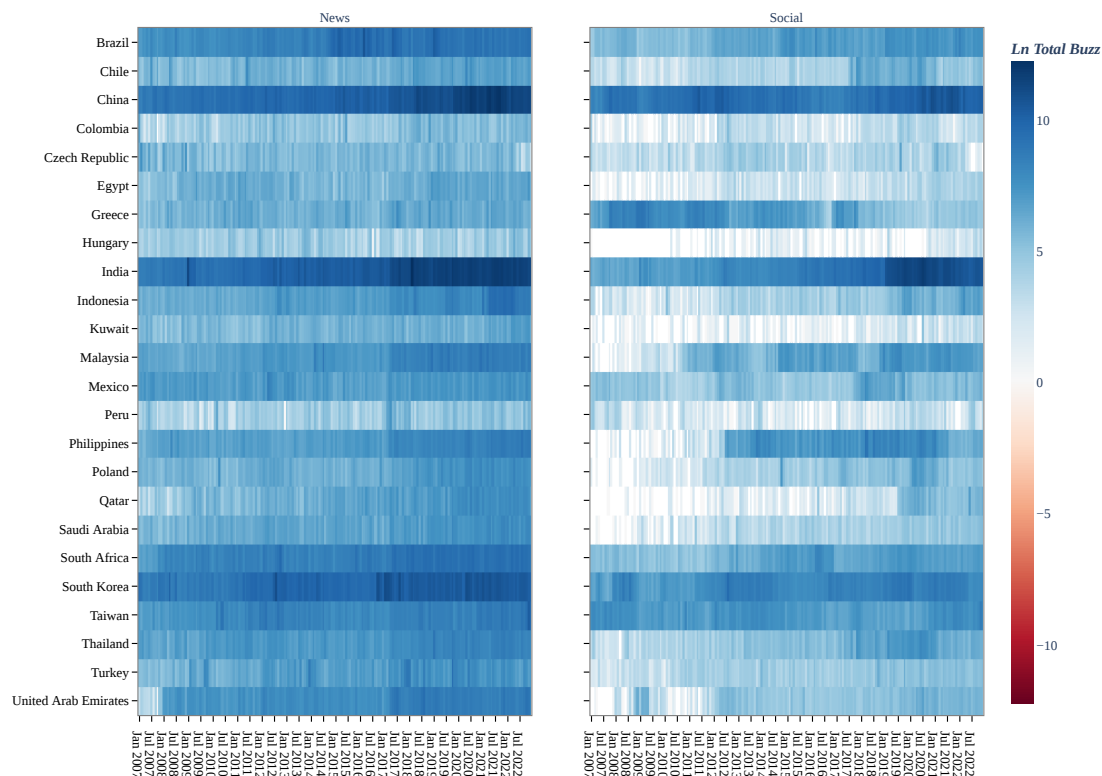
FIGURE 2.5: **Media attention - Developed markets.** This figure presents the level discussion on ESG related topics in *News* media (LHS) and *Social* media (RHS) for Developed market economies. Media attention is measured as the Total *Buzz* generated by each country in each month-year and is presented on a logarithmic scale. Countries are classified as Developed economies based on MSCI Developed Markets index classification accessed in April 2024. Sample period is from January 2007 to December 2021.



an interesting deviation from recent findings in the literature (see Gan et al., 2020) which points to social media overtaking news media as the preferred news medium. Due to the differences in content curation and accessibility, social media is often viewed as having a ‘democratising’ effect on the dissemination of information and the facilitation of public discussion. It is surprising therefore the discussion of ESG topics bucks this trend, however it may point to competing interest of the public depending on the topic of discussion and the type of media consumed. This suggests that social media may not be as influential as news media as it relates to companies and ESG. It therefore poses a broader question of whether information events on environmental, social and governance topics in news and social media behave in the same manner as information events more broadly.

Figures 2.7 to 2.9 summarises the sentiment trend for Developed markets broken down into their Environmental, Social and Governance components (respectively). Meanwhile, figures 2.10 to 2.12 summarises the same but for Emerging markets. In a similar manner to Figures 2.5

FIGURE 2.6: **Media attention - Emerging markets.** This figure presents the level discussion on ESG related topics in *News* media (LHS) and *Social* media (RHS) for Emerging market economies. Media attention is measured as the Total *Buzz* generated by each country in each month-year and is presented on a logarithmic scale. Countries are classified as Emerging economies based on the MSCI Emerging Market index classification accessed in April 2024. Sample period is from January 2007 to December 2021.

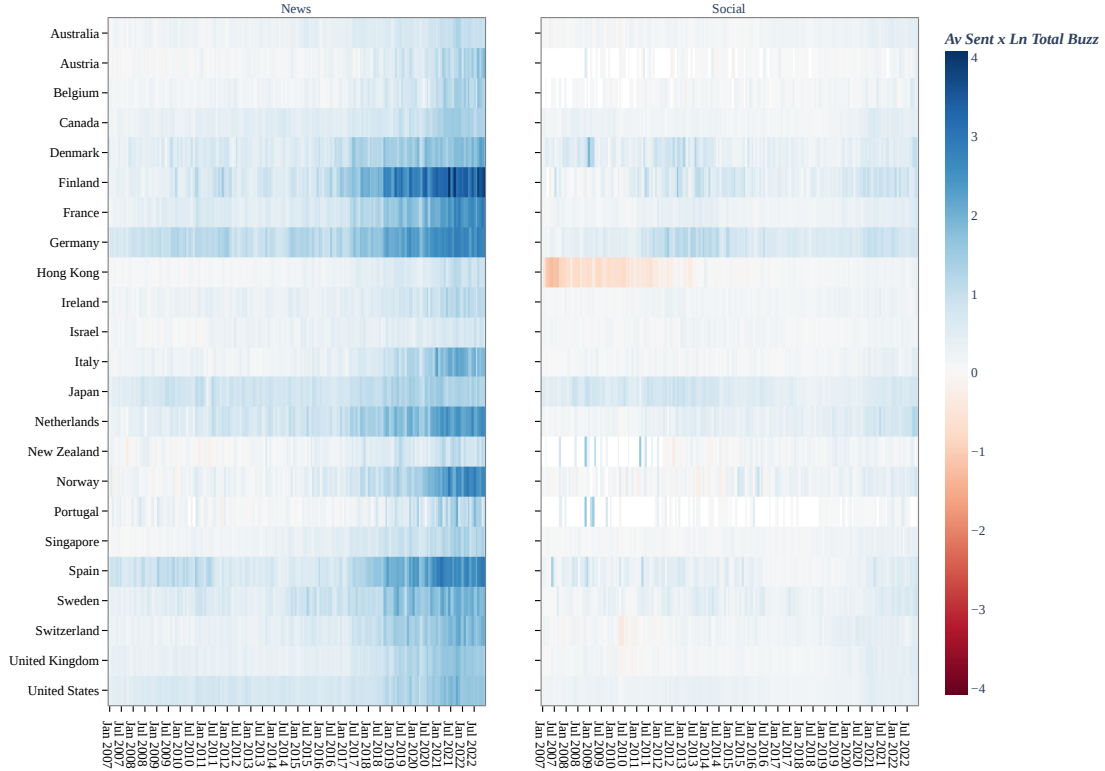


and 2.6, sentiment from news (social) media are presented on the left (right) hand sides. We are mindful that the sentiment variable is normalised such that it is bounded between -1 and 1. However, by its construction, it is not reflective of the attention that contributed to that sentiment value. In other words, a highly negative sentiment value of -1 could have equally been derived from a *Buzz* value of 1 as 1000. In our view, the sentiment score derived from the higher *Buzz* score is of greater value as it indicates stronger public consensus. Therefore, in presenting sentiment, we interact the average daily sentiment i with the logarithm of Total *Buzz* for the month-year period t , country j , and media source k :

$$Sent_{t,j,k} = \left(\frac{1}{N} \sum_i Sent_{i,j,k} \right) \times \ln \sum_i Buzz_{i,j,k} \quad (2.7)$$

It is interesting to observe that for both Developed and Emerging markets, sentiment on topics belonging to the Governance pillar are both strongly negative compared with Environmental and

FIGURE 2.7: **ESG Sentiment in Developed Markets - Environmental topics.** This figure presents the sentiment in developed markets on environmental topics in *News* media (LHS) and *Social* media (RHS). Sentiment is presented here as the interaction of the average sentiment and $\ln Buzz$ for each country in each month-year. Average sentiment is calculated as the weighted average of the *Sent* category variables in each pillar. Countries are classified as Developed economies based on the MSCI Developed Markets Index accessed in April 2024. Sample period is from January 2007 to December 2021.



Social pillars. We also detect that in Developed markets, discussion relating to Environmental and Social issues have generally trended more positive over time, with the sentiment change most apparent in News media. The trend is similar for Emerging market economies, but for the Environmental pillar in News and Social media, and for Social topics in News media only.

FIGURE 2.8: **ESG Sentiment in Developed Markets - Social topics.** This figure presents the sentiment in developed markets on social topics in *News* media (LHS) and *Social* media (RHS). Sentiment is presented here as the interaction of the average sentiment and $\ln Buzz$ for each country in each month-year. Average sentiment is calculated as the weighted average of the *Sent* category variables in each pillar. Countries are classified as Developed economies based on the MSCI Developed Markets Index accessed in April 2024. Sample period is from January 2007 to December 2021.

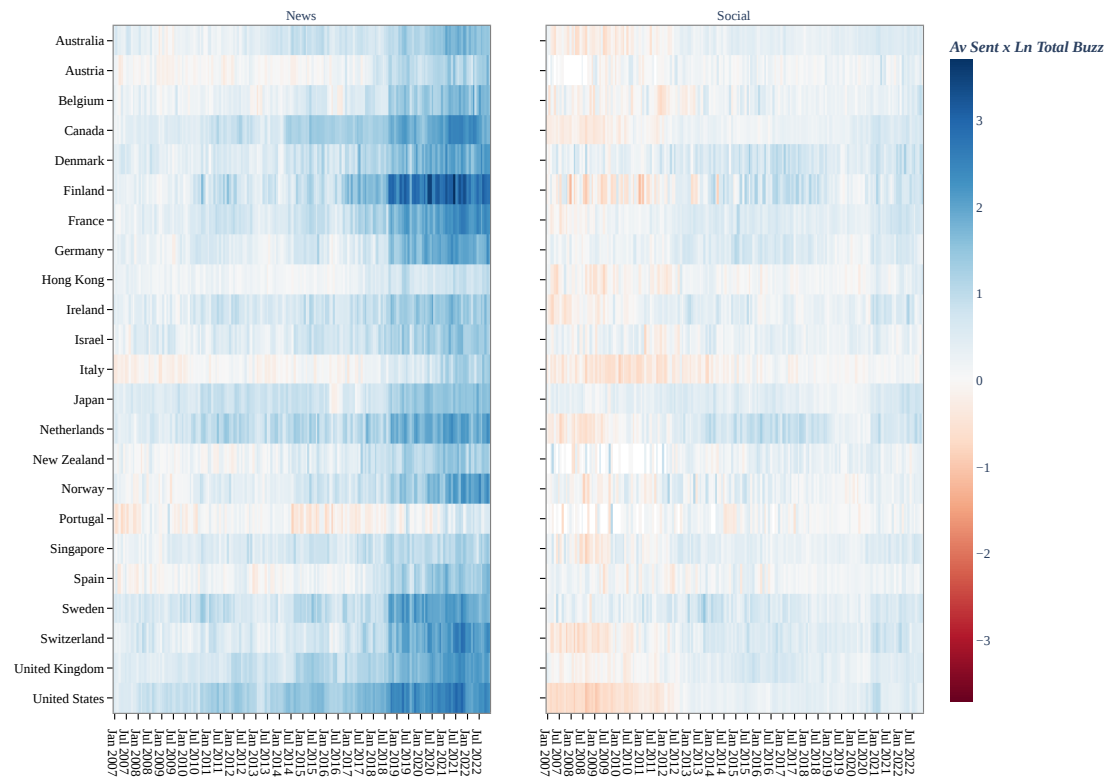


FIGURE 2.9: **ESG Sentiment in Developed Markets - Governance topics.** This figure presents the sentiment in developed markets on governance topics in *News* media (LHS) and *Social* media (RHS). Sentiment is presented here as the interaction of the average sentiment and *ln Buzz* for each country in each month-year. Average sentiment is calculated as the weighted average of the *Sent* category variables in each pillar. Countries are classified as Developed economies based on the MSCI Developed Markets Index accessed in April 2024. Sample period is from January 2007 to December 2021.

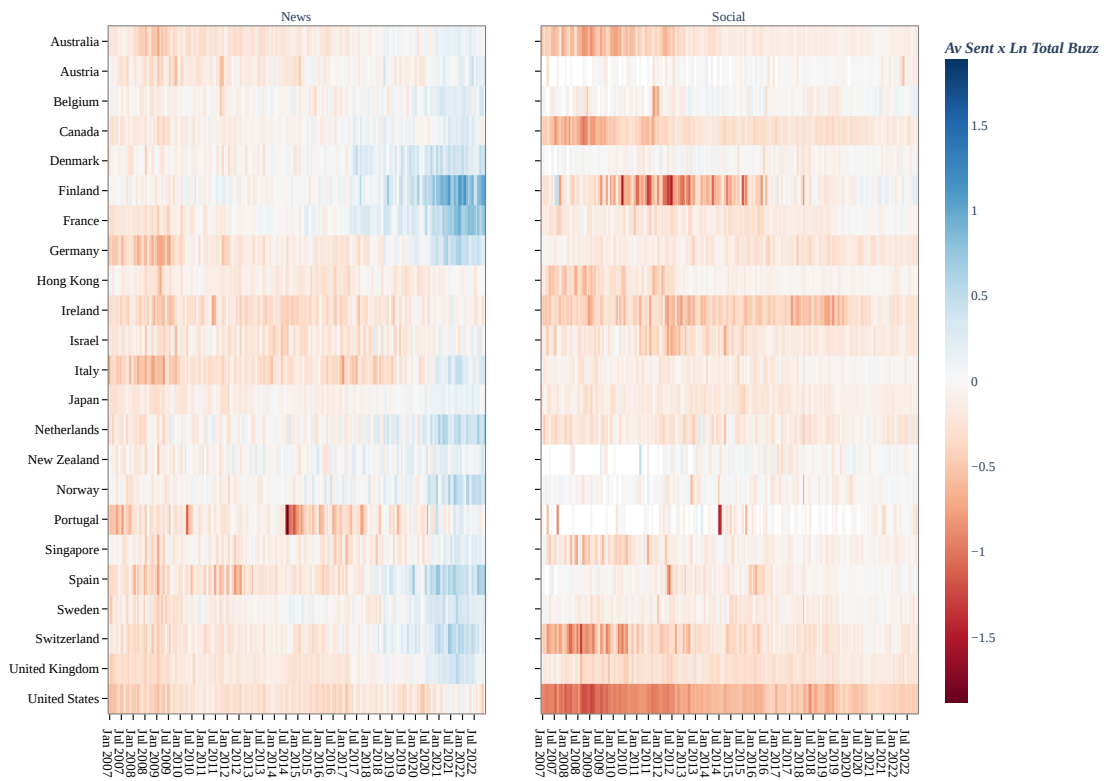


FIGURE 2.10: **ESG Sentiment Emerging Markets - Environmental**. This figure presents the sentiment in emerging markets on environmental topics in *News* media (LHS) and *Social* media (RHS). Sentiment is presented here as the interaction of the average sentiment and \ln *Buzz* for each country in each month-year. Average sentiment is calculated as the weighted average of the *Sent* category variables in each pillar. Countries are classified as Emerging economies based on the MSCI Emerging Markets Index accessed in April 2024. Sample period is from January 2007 to December 2021.

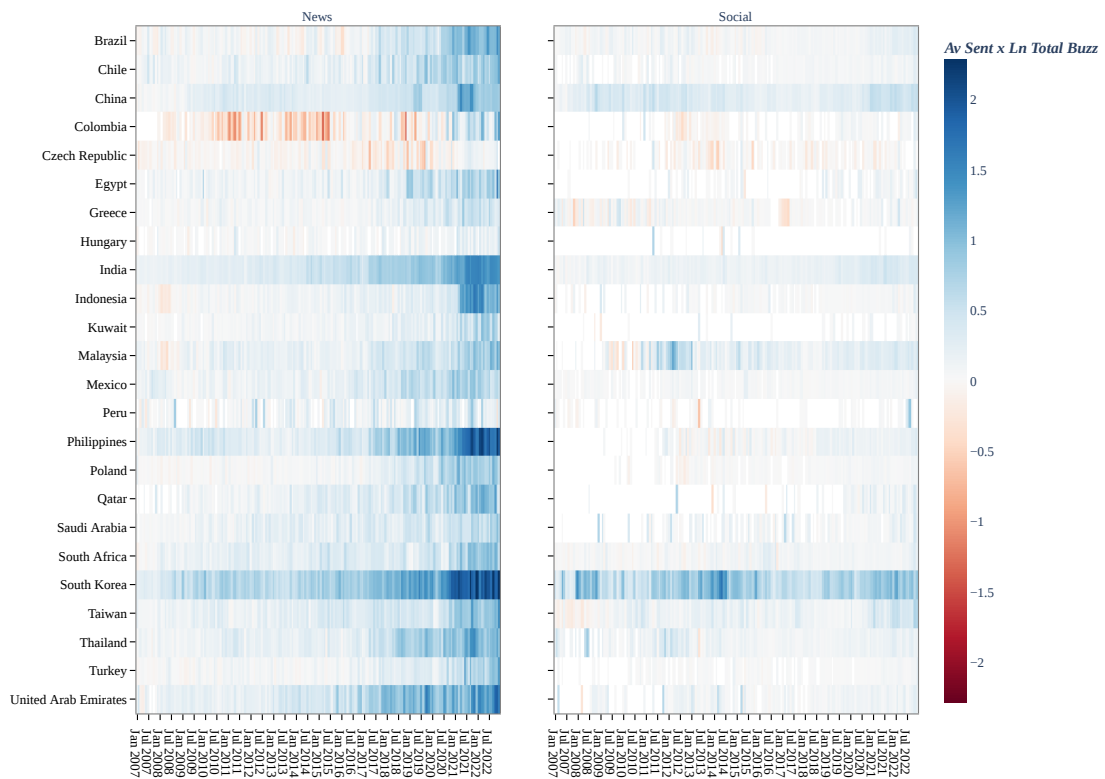


FIGURE 2.11: **ESG Sentiment Emerging Markets - Social.** This figure presents the sentiment in emerging markets on Social topics in *News* media (LHS) and *Social* media (RHS). Sentiment is presented here as the interaction of the average sentiment and $\ln Buzz$ for each country in each month-year. Average sentiment is calculated as the weighted average of the *Sent* category variables in each pillar. Countries are classified as Emerging economies based on the MSCI Emerging Markets Index accessed in April 2024. Sample period is from January 2007 to December 2021.

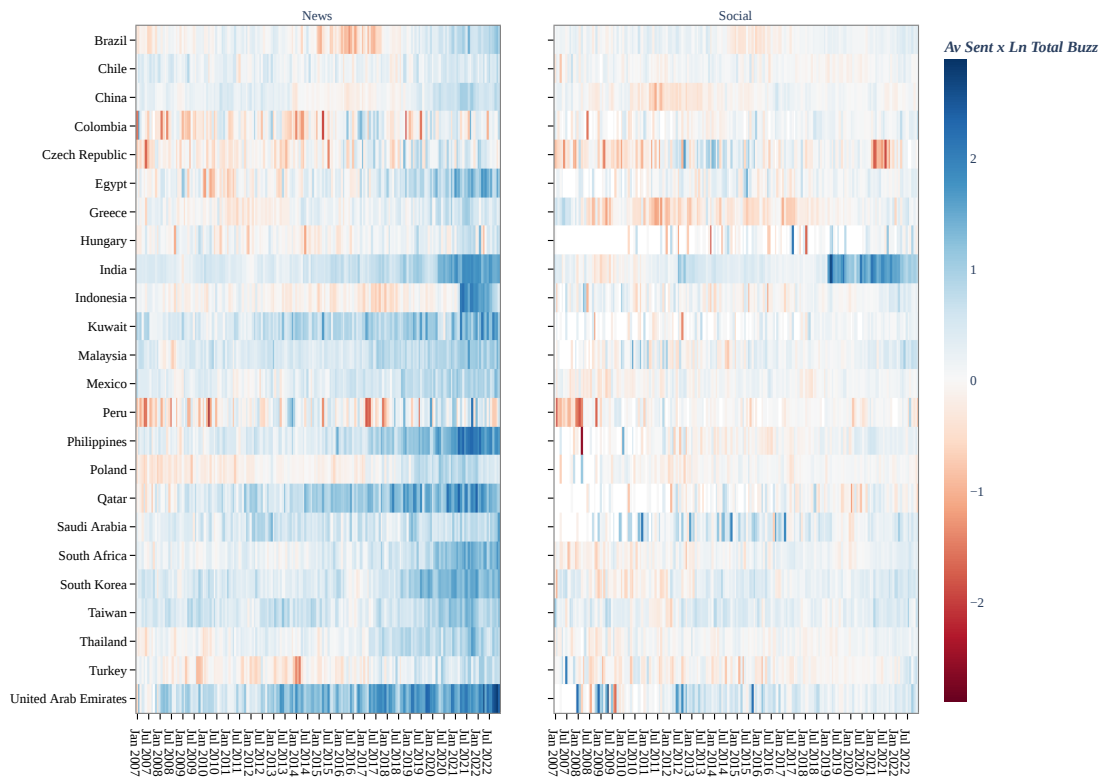
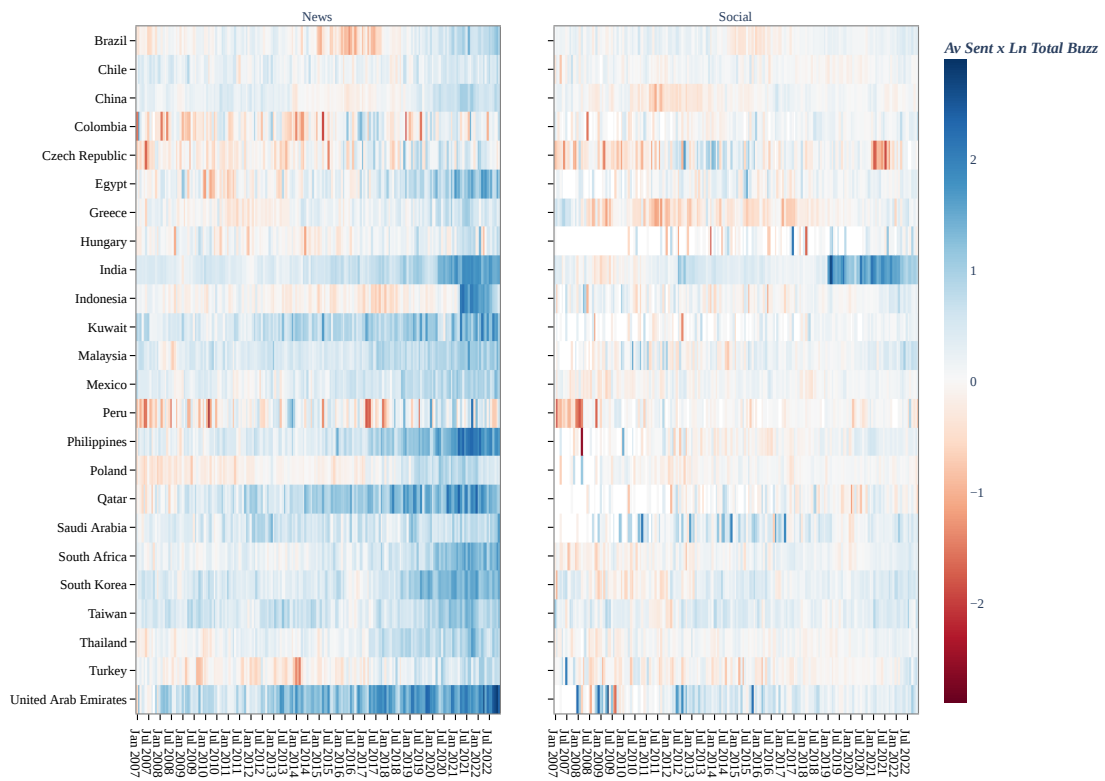


FIGURE 2.12: **ESG Sentiment Emerging Markets - Governance.** This figure presents the sentiment in emerging markets on Governance topics in *News* media (LHS) and *Social* media (RHS). Sentiment is presented here as the interaction of the average sentiment and \ln Buzz for each country in each month-year. Average sentiment is calculated as the weighted average of the *Sent* category variables in each pillar. Countries are classified as Emerging economies based on the MSCI Emerging Markets Index accessed in April 2024. Sample period is from January 2007 to December 2021.



2.4.2 Salient firms

Next we examine the characteristics of salient firms in a single market, the United States, which we choose due to its expansive coverage. In this section we examine some of the drivers of ESG sentiment and in this sense, provide a first look into materiality from a public perspective. We then compare the *Buzz* and *Sent* variables from news and social media for each E, S and G pillar with some common stylised facts of sentiment and the impact they may have on market variables. Finally, we compare our measure of ESG sentiment with Traditional measures of ESG. In performing the above analyses, we investigate our main research questions, respectively: (1) How does ESG sentiment compare with stylised facts of sentiment, and (2) How does ESG sentiment compare with Traditional ESG scores?

2.4.2.1 Defining salient companies

Salient companies are defined as companies that are most prominent in people’s minds, be it due to their size, prominence in a market, or the level of attention received from investors (Akhtar et al., 2012). Using this definition of salience, we draw parallels between the *Buzz* variable, which measures the volume and intensity of ESG related media attention, and salient companies as it relates to ESG. We are careful to distinguish our meaning of the word “salient” in this context from other descriptions in the ESG literature, where saliency has come to imply “preferences for ESG”.¹¹ By our meaning, we assume that if a company is not being talked about on one or more ESG topics, or if an ESG topic is not broadly discussed, then in the public’s view it is not important, and therefore not salient. Our focus on salient companies ensures there is sufficient data for analysis to be undertaken, but has the added benefit of providing a first look into materiality from a public perspective.

To create our sample of salient companies, we start by extracting all US domiciled companies from the RMEA database in the period between 01-Jan-2016 and 31-Dec-2021.¹² We then calculate the total $Buzz_{j,k,t}$ for each firm j , media type k , and month-year t , in our sample and remove any companies that did not record a *Buzz* value for any given month-year. Our aim in this step is to balance volume with consistency, that is, finding companies that are regularly discussed in the media as opposed to those with high volumes of discussion infrequently. Calculating the monthly total *Buzz* allows us to smooth the non-synchronicity of information arrival. Removing

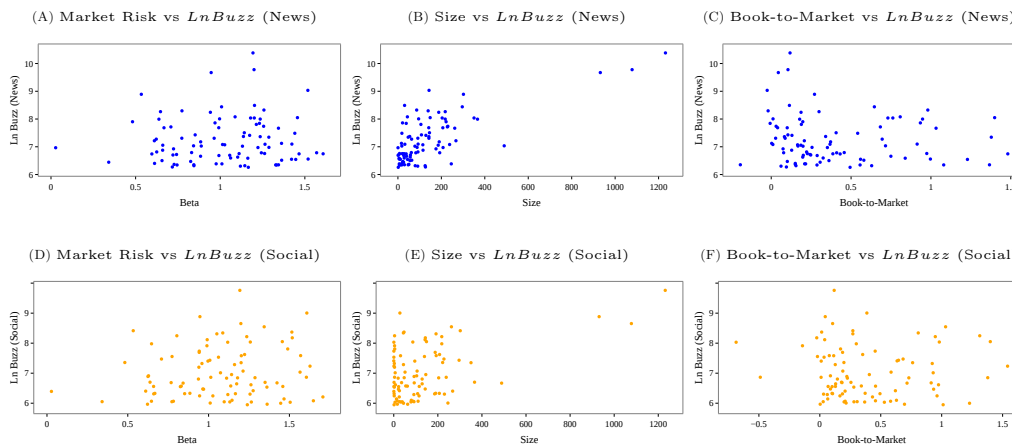
¹¹In terms of ESG, saliency has also come to include companies that possess desirable ESG characteristics (see Cao et al., 2023).

¹²Our sample period is constrained due to our use of the 1-minute files to reconstruct daily *Sent* and *Buzz* signals per the data aggregation methods outlined in Section 2.3.3.

companies that were not discussed in a given month-year ensures that we avoid companies that may have attracted high volumes of discussion but for only a small portion of the sample period. Removing companies on this criterion dramatically reduces the sample available from 6,123 (5,972) to 339 (261) companies in news (social) media. We then select 100 companies with the highest average monthly *Buzz* in news and social media.

Figure 2.13 plots Market Risk (left panel), Size (middle panel), and Book-to-Market (right panel) against $\ln(\text{Buzz})$ for News (top panel) and Social Media (bottom panel) to examine whether common firm characteristics are associated with media attention in the sample of salient companies. Size indicates a positive linear relationship with *Buzz*, with the effect being more pronounced for news than for social media. This suggests that larger companies tend to attract greater media attention, which is consistent with the definition of salience outlined above. By contrast, Book-to-Market shows a negative relationship with *Buzz*, indicating that growth firms (low Book-to-Market) receive more media attention than value firms (high Book-to-Market), again with the effect stronger for news than for social media. In contrast, no meaningful relationship is observed between Market Risk and media attention.

FIGURE 2.13: **Factor characteristics of salient firms.** This figure presents the relationship of common firm characteristics (x-axis): Market Risk (Beta), Size, and Book-to-Market vs $\ln \text{Buzz}$ (y-axis). Beta is computed as the daily returns of each salient firm regressed against the daily returns of the S&P500 (the market proxy). Size is presented as Market Capitalisation (in billions). Book-to-Market is computed as Shareholder Equity divided by Market Capitalisation.



2.4.2.2 Distributional characteristics

Table 2.3 presents the summary statistics of the resulting salient companies broken down into the Thomson Reuters Business Classification (TRBC) Economic industry groups. Panel A presents the statistics for companies deemed salient in news media, whilst Panel B presents the same but

for social media.

TABLE 2.3: **Summary Statistics of *Buzz* for Salient Firms.** This table presents the distribution of the daily *Buzz* variable for the 100 most salient public and private firms in the US market. Panel A presents the summary obtained from news media whilst Panel (B) presents the same but from social media. *Buzz* captures the volume and intensity of discussion on ESG topics and is our proxy for the level of ESG media attention. To determine salient stocks from each media type, we first calculate the total monthly $Buzz_{j,k}$ for each US firm j and media type k , and remove firms that did not generate *Buzz* in any given month-year of the sample period. We then find the average total *Buzz* of the remaining firms, then sort from highest to lowest. The most salient firms are taken as those with the highest average *Buzz*. The sample period is from 01-Jan-2016 to 31-Dec-2021.

Panel A: News									
	# Companies	# Obs	mean	std	min	25%	median	75%	max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
All	100	196,313	108.86	324.45	0.5	11.0	32.0	83.5	14,699.0
Basic Materials	2	3,657	27.34	38.41	0.5	6.0	15.5	34.0	705.0
Consumer Cyclical	21	41,642	119.20	377.78	0.5	9.5	28.0	75.0	10,716.0
Consumer Non-cyclical	8	16,190	82.06	192.44	0.5	12.0	32.5	84.5	9,113.0
Energy	6	11,490	92.39	219.50	0.5	12.0	36.0	96.0	6,534.0
Financials	17	32,071	65.58	193.63	0.5	8.0	24.0	62.0	10,423.5
Healthcare	7	13,746	87.77	275.88	0.5	9.0	24.0	62.0	9,663.5
Industrials	18	36,399	84.83	274.13	0.5	12.0	32.0	77.0	14,699.0
Technology	13	26,957	232.95	526.48	0.5	21.0	62.0	171.5	9,834.5
Telecommunication Services	2	4,287	87.16	135.50	0.5	24.0	52.0	100.2	2,952.0
Utilities	6	9,874	87.71	219.93	0.5	9.0	30.5	85.0	7,122.5
Panel B: Social									
	# Companies	# Obs	mean	std	min	25%	median	75%	max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
All	100	196,827	59.16	177.47	0.5	8.5	22.5	53.0	20,972.0
Basic Materials	3	4,985	22.66	34.28	0.5	4.0	11.0	27.5	607.0
Consumer Cyclical	21	42,053	65.12	273.99	0.5	9.0	22.5	47.0	20,972.0
Consumer Non-cyclical	7	14,675	50.50	84.79	0.5	9.0	21.5	58.0	4,751.0
Energy	8	15,823	49.16	93.15	0.5	8.0	22.5	55.0	3,186.5
Financials	12	23,320	47.48	110.04	0.5	7.0	19.5	46.0	5,980.0
Healthcare	12	23,743	50.91	143.19	0.5	8.0	19.5	46.0	11,234.5
Industrials	10	20,850	39.65	100.60	0.5	7.5	17.5	38.0	4,398.0
Technology	22	42,629	87.80	199.55	0.5	11.0	33.0	81.0	17,241.5
Telecommunication Services	3	5,344	50.71	62.43	0.5	18.0	39.5	63.5	912.0
Utilities	2	3,405	34.63	100.00	0.5	4.0	10.0	28.5	2,287.0

This table yields some interesting insights. In terms of saliency, we observe that companies within the Industrials and Financial industry groups more likely to be discussed in news media than in social media, whilst Technology companies more likely to be discussed in social media. This is perhaps not surprising given the nature of these industry types, highlighting preferences on the communication channels that investors prefer to engage with for these industries. In all cases, we find that the *Buzz* variable is highly positively skewed with the mean greater than the median and long tails evident, thereby warranting normalisation treatment of the variable before use in statistical analysis.

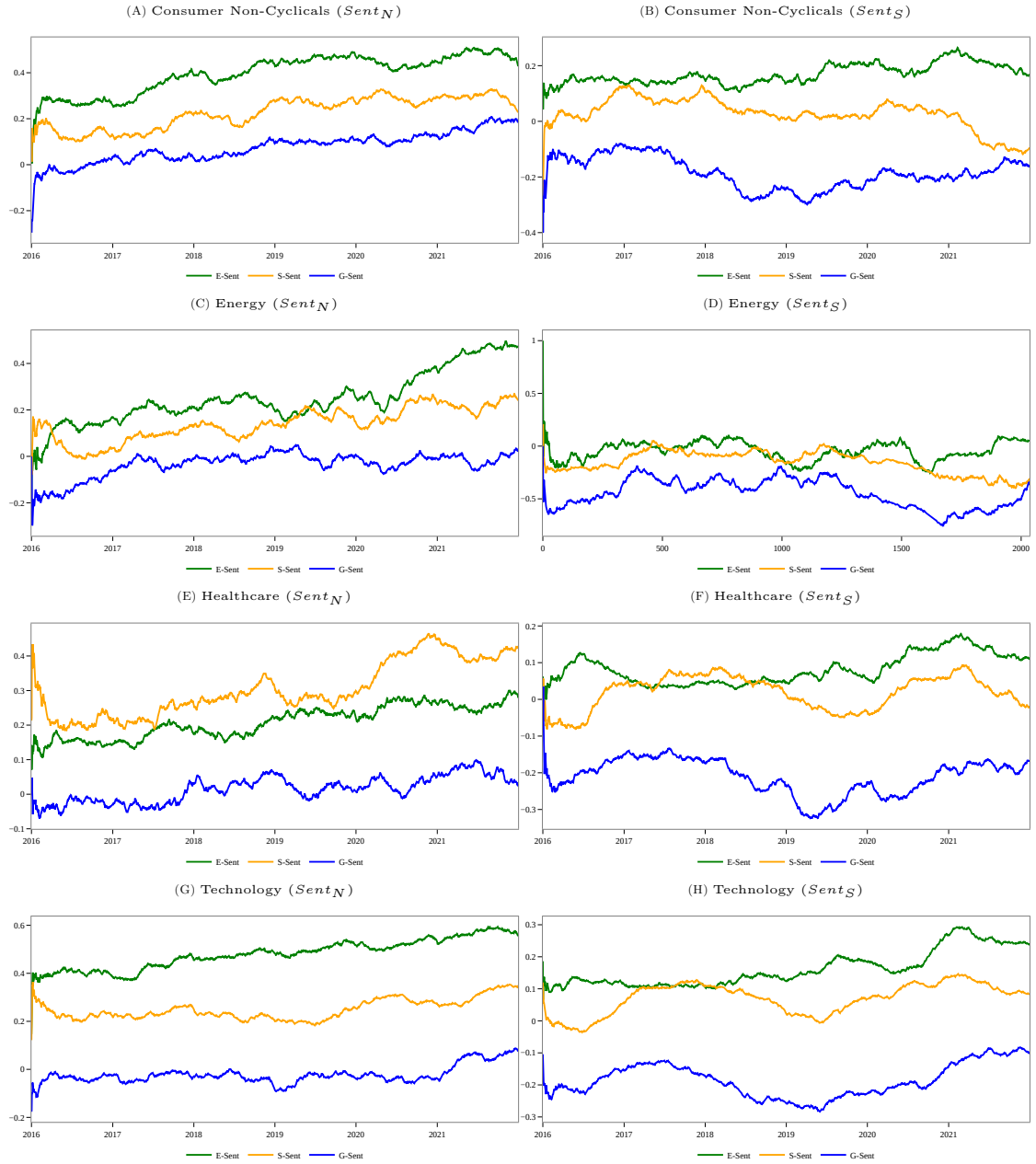
Most interesting however are the notable differences in the distributional characteristics of *Buzz* between news and social media. Whilst the number of observations appear to be similar between the two media types, the average volume is far greater in news media with a mean *Buzz* value of 108.86 compared with 59.16 for social media with the differences most prominent

for Consumer Cyclical (119.20 vs 65.12), Technology (232.95 vs 87.80) and Utilities (87.71 vs 34.63). The standard deviation for all salient companies is almost double in news media (324.45) compared with social media (177.47). Across the industry groups the standard deviation ranges between 38.41 for Industrials and 526.48 for Technology in news media, and 34.28 for Basic Materials and 273.99 for Consumer Cyclical in social media. Surprisingly, the maximum values are in most cases larger in social media, pointing to both a greater incidence of isolated extreme discussion events in social media channels, and a greater consistency of high volume discussion in news media.

2.4.2.3 Sentiment

We now examine the sentiment generated in media discussion on our sample firms. For brevity, Figure 2.14 presents the average sentiment of salient firms over the sample period for four industry groups; Consumer Non-Cyclical, Energy, Healthcare, and Technology. We observe that in most cases, the sentiment on environmental discussion is generally more positive than governance in both news and social media. This is particularly evident for the Consumer Non-Cyclical and Technology groups. A slight positive trend in sentiment is also observed which appears most predominantly for the environmental pillar in news media for all the selected industry groups. The positive trend detected is consistent with findings in the literature which point to improvements in ESG performance in particular in the Environmental and Social pillars (see Daugaard and Ding, 2022).

FIGURE 2.14: **Sentiment Trend.** This figure plots the average daily sentiment, $Sent$, for companies in the following TRBC Economic Industry groups: Consumer Non-Cyclicals, Energy, Healthcare, and Technology for news (LHS) and social media (RHS). The daily $Sent$ variable was reconstructed from 1-minute observations between 09:35 on day t to 09:25 on day $t + 1$ to capture overnight sentiment. Observations in the 5-min immediately following (preceeding) market open are excluded to avoid volatility impacts associated with the opening session. Sample period is between 01-Jan-2016 and 31-Dec-2021



We explore the extent to which positive sentiment outweighs negative sentiment by computing the ratio of positive to negative observations for the sample firms in each ESG category in our dataset, grouped by TRBC Economic Sector for news and social media. Figure 2.15 illustrates a stronger positive bias in ESG discussion in news media, particularly in the environmental categories of *emissions* and *environmentalInnovation*, and the social categories of *humanRights* and *product*. By comparison, in social media, a strong positive bias was detected in the Utilities sector for *environmentalInnovation* and *humanRights*.

2.4.2.4 Materiality

We now break down media attention into their respective categories to get a sense of what drives *Buzz* and to find out what the public deems to be material. Until recently, materiality as it relates to ESG, has been narrowly defined in terms of financial materiality, in other words, the risks or opportunities that ESG poses to a firm's bottom line (see Serafeim, 2020; Delgado-Ceballos et al., 2023). Figure 2.16 provides a visual snapshot of financial materiality across 26 sustainability issues for mining, materials and energy sub-industry groups as classified by the Sustainable Accounting Standards Board (SASB).¹³ We can see from this figure that sustainability items relating to the environment feature heavily as being financially material to companies within these sub-industries, where positive (negative) disclosures are likely to add (detract) from shareholder value. Financial materiality therefore corresponds with the notion of Value-Based investing. While the focus on issues affecting a company's bottom line was initially to improve sustainability more broadly, doubts have surfaced as to whether financial materiality alone can mitigate the negative externalities imposed on the environment by company activities.

The concept of double materiality was first formally proposed by the European Commission (European Commission, 2019) in outlining the disclosure requirements on activities that are likely to have an environmental or societal impact in addition to those that impact on investors. This was in broad recognition that company activities despite there being no impact on shareholder value, may still be detrimental to non-financial stakeholders (Adams et al., 2021; Delgado-Ceballos et al., 2023).

The methods used to determine societal materiality include mapping disclosures to SDG's, however this still suffers from the untimely lags from when they occur to when the information is made available. Sentiment indicators however may provide a more timely approach. Figure 2.17 presents a concept of materiality by public opinion from news (Panel (A)) and social media (Panel

¹³Now the International Sustainability Standards Board (ISSB) of the IFRS Foundation.

(B)) sources broken down by RMEA category and TRBC Economic Industry group. Unlike qualitative approaches taken to determine societal materiality, materiality by public opinion is determined solely from the amount of media attention a topic receives. In both news and social media it is clear to see that issues relating to the *community* category (such as *anger*, *trust*) present as most material across all industries, whilst environmental concerns are most prominent for companies in the Energy and Utilities industry.

FIGURE 2.15: **Positive bias in news and social media.** This figure presents the ratio of positive to negative observations detected in news (Panel (A)) and social media (Panel (B)) broken down into their respective categories (x-axis) and industry groups (y-axis). The RMEA category *CSRStrategy* is excluded as it is exclusively positive. The colour scale is capped at 10:1 to aid visualisation.

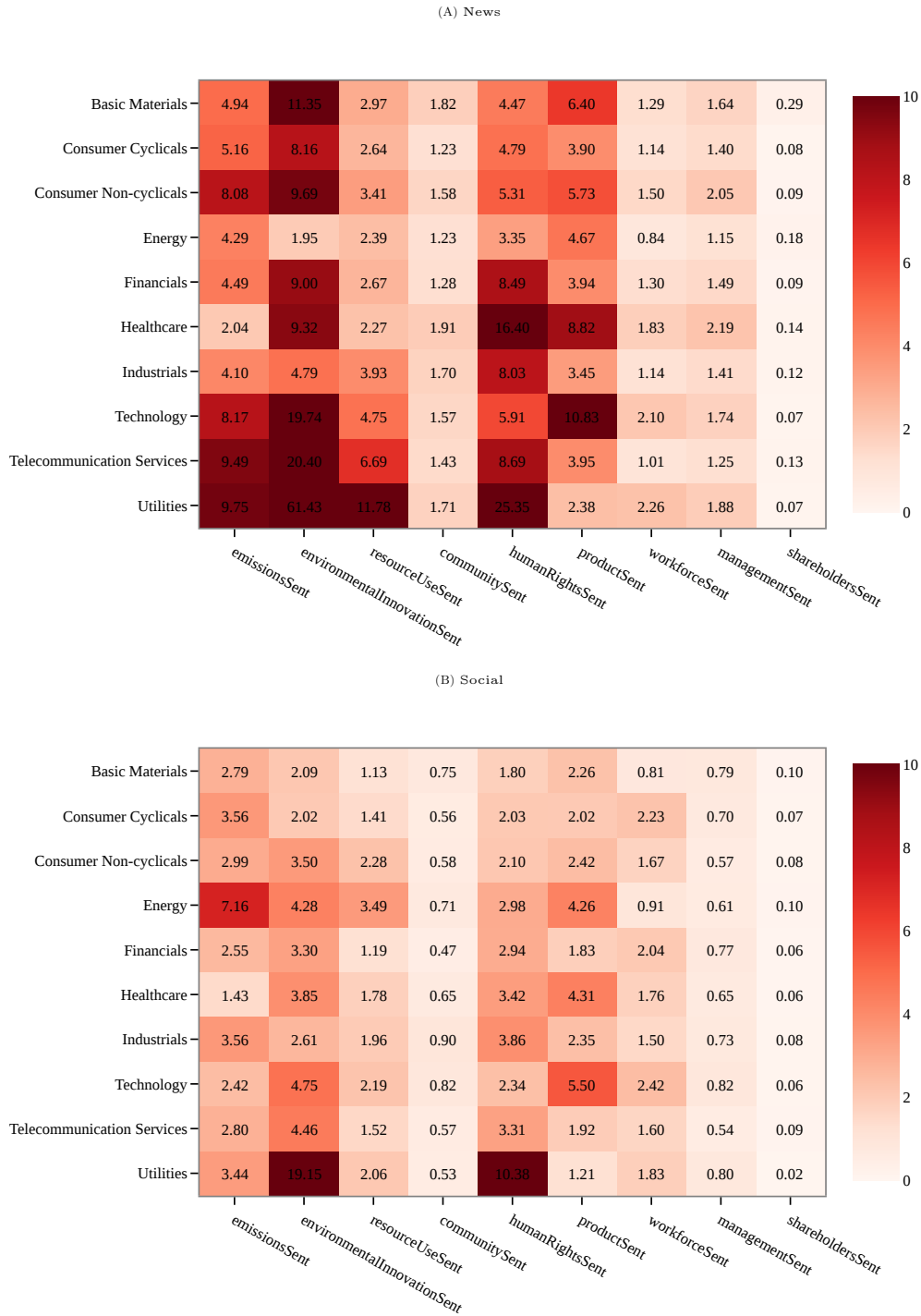
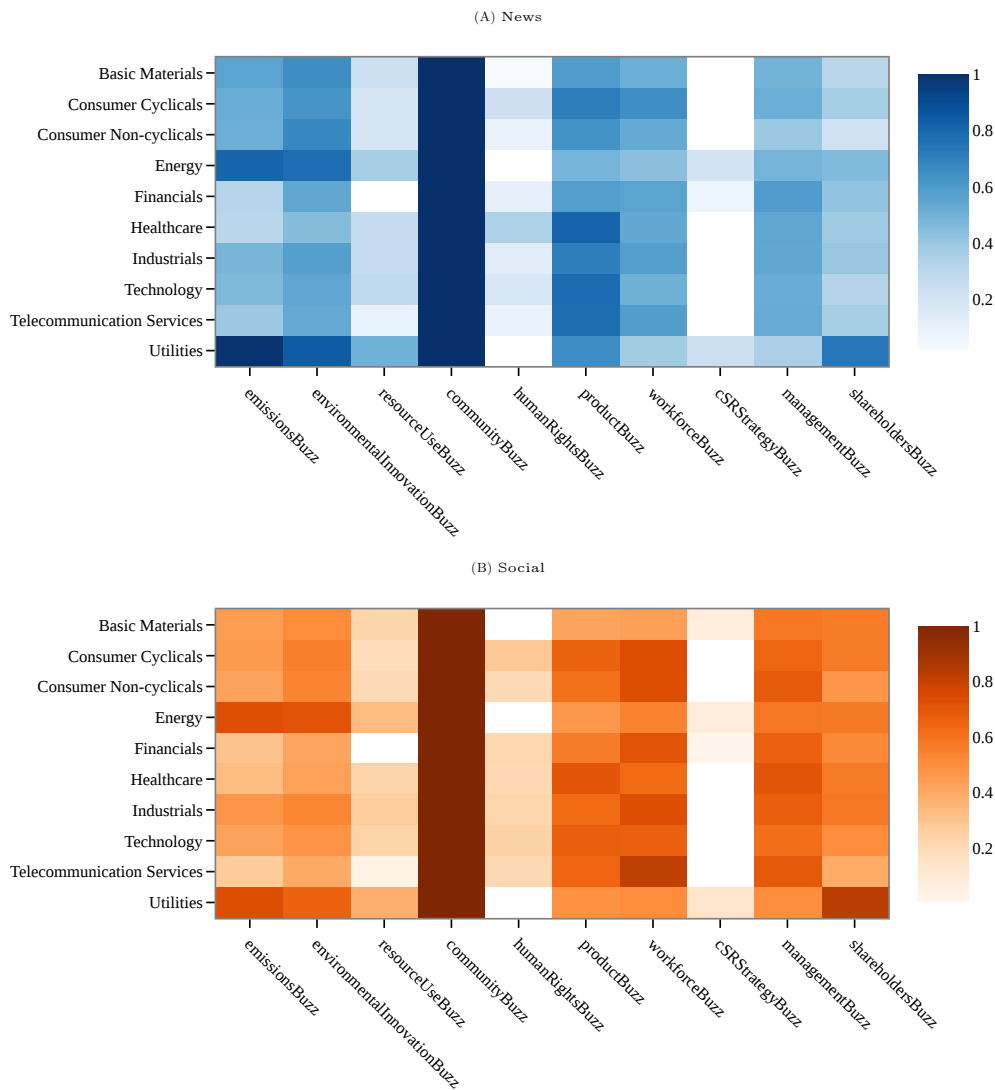


FIGURE 2.16: **Financial Materiality.** Excerpt of the financial materiality matrix extracted from the Sustainable Accounting Standards Board (SASB) <https://sasb.ifrs.org/standards/materiality-map/>

		Consumer Goods	Extractives & Minerals Processing								Financials	Food & Beverage	Health Care	Infrastructure
Dimension	General Issue Category ¹⁾	Click to expand	Coal Operations	Construction Materials	Iron & Steel Producers	Metals & Mining	Oil & Gas – Exploration & Production	Oil & Gas – Midstream	Oil & Gas – Refining & Marketing	Oil & Gas – Services	Click to expand	Click to expand	Click to expand	Click to expand
Environment	GHG Emissions		■	■	■	■	■	■	■	■		■	■	■
	Air Quality			■					■	■				■
	Energy Management	■												
	Water & Wastewater Management	■	■				■		■	■		■		■
	Waste & Hazardous Materials Management	■	■						■	■		■		■
Social Capital	Ecological Impacts		■	■			■	■	■	■		■		■
	Human Rights & Community Relations		■				■	■	■	■		■		■
	Customer Privacy	■									■	■	■	■
	Data Security	■									■	■	■	■
	Access & Affordability	■									■	■	■	■
Human Capital	Product Quality & Safety	■									■	■	■	■
	Customer Welfare										■	■	■	■
	Selling Practices & Product Labeling										■	■	■	■
	Labor Practices	■	■			■					■	■	■	■
	Employee Health & Safety	■	■			■					■	■	■	■
Business Model & Innovation	Employee Engagement, Diversity & Inclusion	■					■		■	■	■	■	■	■
	Product Design & Lifecycle Management	■	■	■					■	■	■	■	■	■
	Business Model Resilience	■	■				■				■	■	■	■
	Supply Chain Management	■	■								■	■	■	■
	Materials Sourcing & Efficiency	■	■	■							■	■	■	■
Leadership & Governance	Physical Impacts of Climate Change										■	■	■	■
	Business Ethics										■	■	■	■
	Competitive Behavior										■	■	■	■
	Management of the Legal & Regulatory Environment						■	■	■	■				■
	Critical Incident Risk Management						■	■	■	■				■
	Systemic Risk Management									■				■

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FIGURE 2.17: **Materiality based on public opinion.** This figure presents the sum of all *Buzz* generated for each ESG category (x-axis) and TRBC Economic Industry group (y-axis) for firms in our sample over the sample period. Panel (A) presents for News media whilst Panel (B) presents for Social media. The sample period is from 01-Jan-2016 to 31-Dec-2021.



2.4.3 Stylised Facts

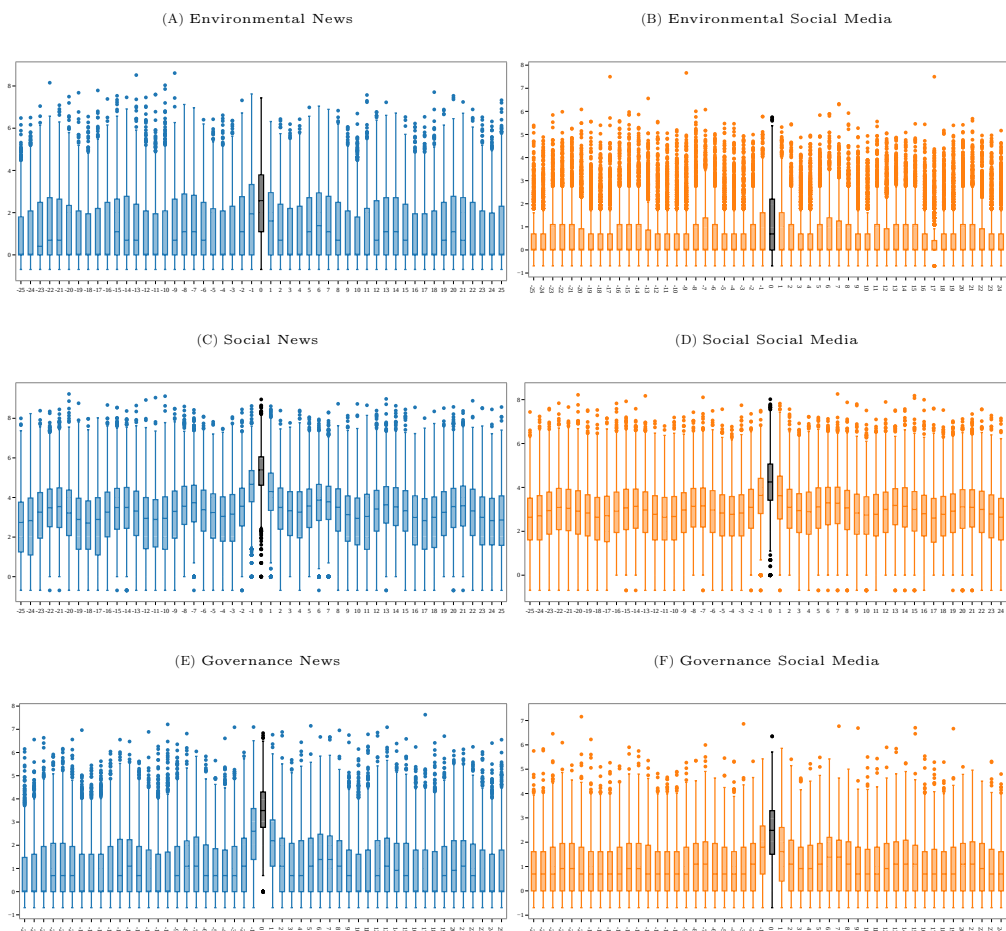
In this section we test the RMEA *Buzz* and *Sent* variables against often observed properties of sentiment data. Our reason for doing so is two-fold. First, we aim to determine whether isolating sentiment into a specific topic (such as Environmental, Social or Governance) results in the same properties being captured in previous studies of sentiment. Our starting hypothesis is that stylised facts of sentiment should be satisfied regardless of the topic that is driving that sentiment. With the RMEA database, we have a unique opportunity test this theory as sentiment has been decomposed into specific buckets. Second, we aim to determine if there exist differences in the informational content between news and social media. We conduct an empirical analysis of two prominent stylised facts: (1) the surge in news volume surrounding earnings announcements and (2) the asymmetric response to news, first identified by Tetlock et al. (2008) in their influential study which quantified the relationship between media coverage and market reaction.

Stylised Fact 1: media coverage around earnings announcements

In Figure 2.18 we replicate the media coverage around earnings announcements figure from Tetlock et al. (2008) by aggregating *Buzz* across our sample firms over the 25 days preceding and following the earnings announcement date, the announcement date itself. It is important to note that unlike Tetlock et al. (2008), *Buzz* is only counted once relative to its position to the earnings announcement date. However, instead of plotting the accumulated volume, we include the distributional characteristics of $\ln Buzz$ on these days using a box plot similar to Arratia et al. (2021).

The Social and Governance pillars in both news and social media demonstrate on average, a marked increase in *Buzz* on the day of, and immediately around, the earnings announcement. In contrast, the Environmental pillar experiences a less noticeable rise in volume, particularly on social media where the increase on the day of earnings announcement is minimal. Generally, the findings align with those of Tetlock et al. (2008) and Arratia et al. (2021), indicating a non-random distribution of news and social media coverage on average. However, the box plots capture a randomness in the tails that was not evident in Arratia et al. (2021), suggesting that for discussion on ESG topics, high volumes of media attention can occur at any time and do not appear to be tied to earnings announcements. For discussion on ESG topics at least, this weakens the economic link between media attention and earnings announcements.

FIGURE 2.18: **Media coverage around Earnings Announcements.** This figure illustrates the distribution of *Buzz* for salient companies in the 25 days before and after a company's earnings announcement detected in discussion on Environmental (top panel), Social (middle panel) and Governance (bottom panel) issues. The three panels on the left represent extreme sentiment detected in news media, whilst panels on the right represent extreme sentiment detected in social media. The sample consists of 64 public companies which represent the intersection of companies with the highest monthly average *Buzz* in news and social media after removing companies that recorded zero *Buzz* in any month-year of the sample period. The daily *Buzz* variable is reconstructed from 1-minute observations between the window 09:35 on day t and 09:25 on day $t + 1$. Observations in the 5-minutes following (preceding) the open are excluded to avoid the volatility impacts associated with the market open. The sample period is between 01-Jan-2016 and 31-Dec-2021.



Stylised Fact 2: asymmetric response to news

The question of whether and how markets react to sentiment in ESG news and social media remains unresolved. This inquiry is significant due to the substantial financial stakes involved, amounting to trillions of dollars, and the existence of an entire industry predicated on the concept of sustainable investing. One way to investigate this issue is to examine market activity during periods of intense media attention, particularly focusing on the differential responses to

positive and negative sentiment. The literature extensively documents investor reactions to negative news and the subsequent impact on stock returns. For example Chan (2003) finds that underperforming stocks tend to exhibit continued drift for up to 12 months after a negative news event while Tetlock et al. (2008) observes that (negative) abnormal returns persist for 10 trading days following a positive (negative) news event. Regarding reactions to ESG news, Serafeim and Yoon (2022) finds that stock price reactions to negative ESG news are more pronounced than those for positive news.

Figure 2.19 compares the market response to positive (negative) sentiment on days of extreme *Buzz*, illustrating the cumulative abnormal return (CAR) of a company from 10 trading days prior to an extreme *Buzz* event day to 10 trading days subsequent to it. An extreme *Buzz* event day is defined as a day on which the *Buzz* for a company falls within the 95% percentile of a rolling window of 90 trading days and categorised as either positive or negative sentiment. Events were excluded if they occurred within 10 business days of a previously identified event. In total we identify 7,876 events in news media and 7,152 events in social media across the ESG pillars from 64 companies over the period between 1-Jan-2016 to 31-Dec-2021. We use the three-factor model of Fama and French (1993) with a [-252, -1] day trading day estimation window.

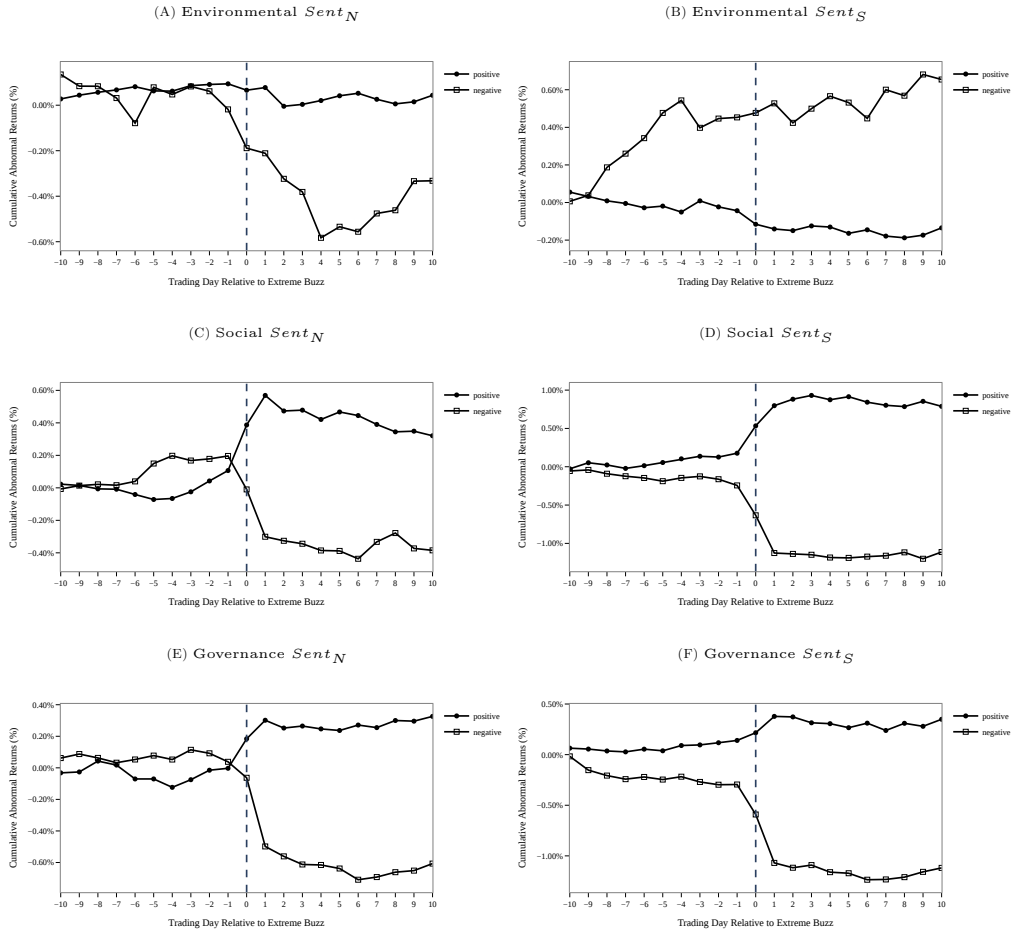
Behaviours observed align with those documented in literature, showing a positive (negative) response when positive (negative) sentiment is detected for extreme *Buzz* events. This holds true in all cases except for the Environmental pillar in social media events, where negative sentiment leads to a positive 50 basis points CAR. Upon investigation, much of the cumulative gain occurs prior to the event suggesting that negative sentiment on environmental topics discussed on social media has only a trivial impact on stock price returns.

A possible reason for this phenomenon may be that although negative sentiment is detected, discussion on social media may be too vague to be financially relevant. For example, several studies show that specific terms relating to topics of “CO2 emissions” and “climate impact” generate the most negative sentiment in social media (Amangeldi et al., 2024). However, these discussions tend to be broad, and although company activities may contribute to increased emissions and climate impact in aggregate, it is difficult to relate a specific event to a financial cost to a company, unlike for an oil spill, where the costs can be identified and attributed to the company.

2.4.3.1 Predictability of RMEA variables

Finally, we wish to examine whether there is predictive power in ESG specific sentiment or media attention in relation to market variables. There is substantial evidence in the literature to

FIGURE 2.19: **Performance around extreme information events.** This figure illustrates the Cumulative Abnormal Return (CAR) in the 10 trading days preceding and following a day of extreme sentiment detected in discussion on Environmental (top panel), Social (middle panel) and Governance (bottom panel) issues. The three panels on the left represent extreme sentiment detected in news media, whilst panels on the right represent extreme sentiment detected in social media. The sample consists of 64 public companies which represent the intersection of companies with the highest monthly average *Buzz* in news and social media after removing companies that recorded zero *Buzz* in any month-year of the sample period. Extreme sentiment is defined as a day on which the *Buzz* variable falls within the 95% percentile of a rolling window of 90 trading days. Events were excluded if they occurred within 10 trading days of a previously identified event. The daily *Buzz* variable is reconstructed from 1-minute observations between the window 09:35 on day t and 09:25 on day $t + 1$. Observations in the 5-minutes following (preceding) the open are excluded to avoid the volatility impacts associated with the market open. Sample period is between 01-Jan-2016 and 31-Dec-2021.

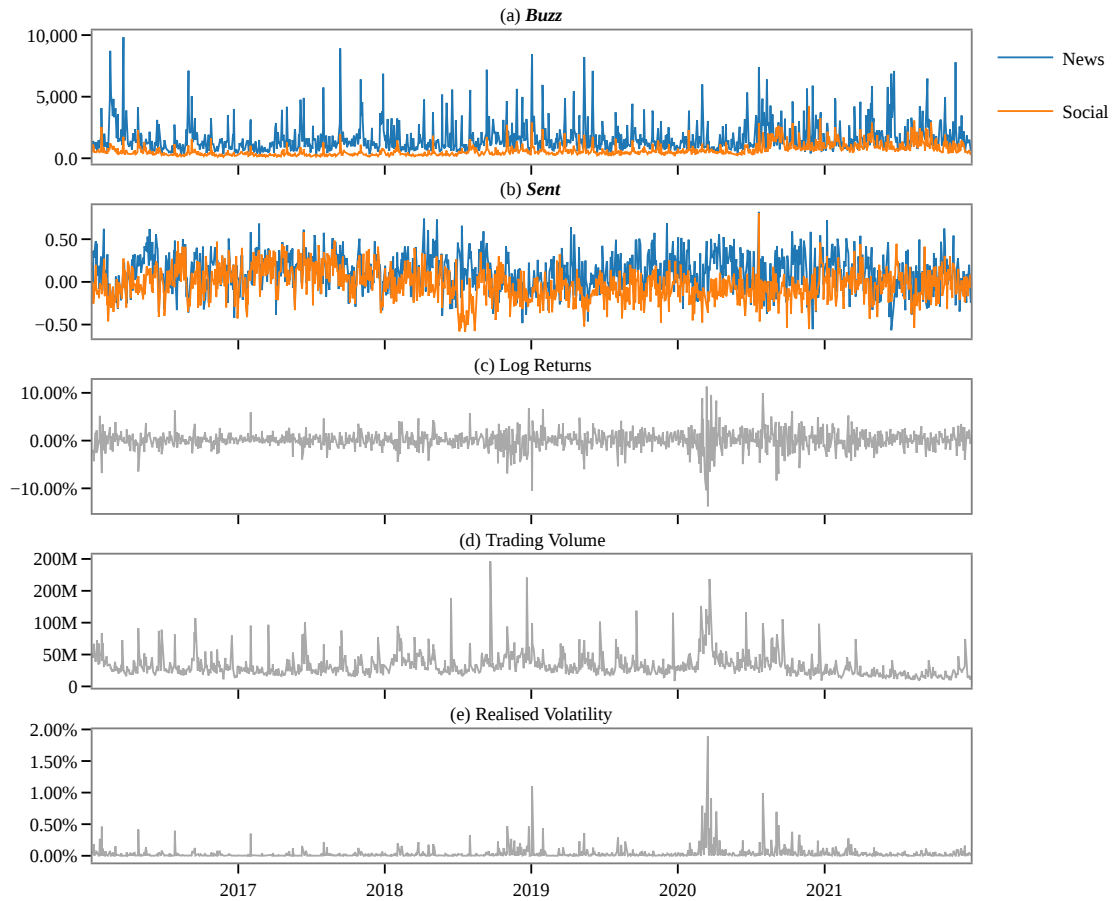


suggest that there should be. Tetlock (2007) for example, was one of the first to associate content in news media with investor sentiment, finding that pessimism in news media led to downward pressure on market prices. More recently, and relevant to our study, Flammer (2013), Kölbel et al. (2017), Capelle-Blancard and Petit (2019), and Serafeim (2020), find a significant effect of ESG related news on stock market activity.

To illustrate the relationship between our proxies for ESG media attention and sentiment against key market variables: $\ln Ret$, $\ln Volume$ and $\ln Ret^2$. Figure 2.20 plots *Buzz* and *Sent*

(Panels (A) and (B) respectively) alongside key market variables for a single salient stock: Apple Inc.

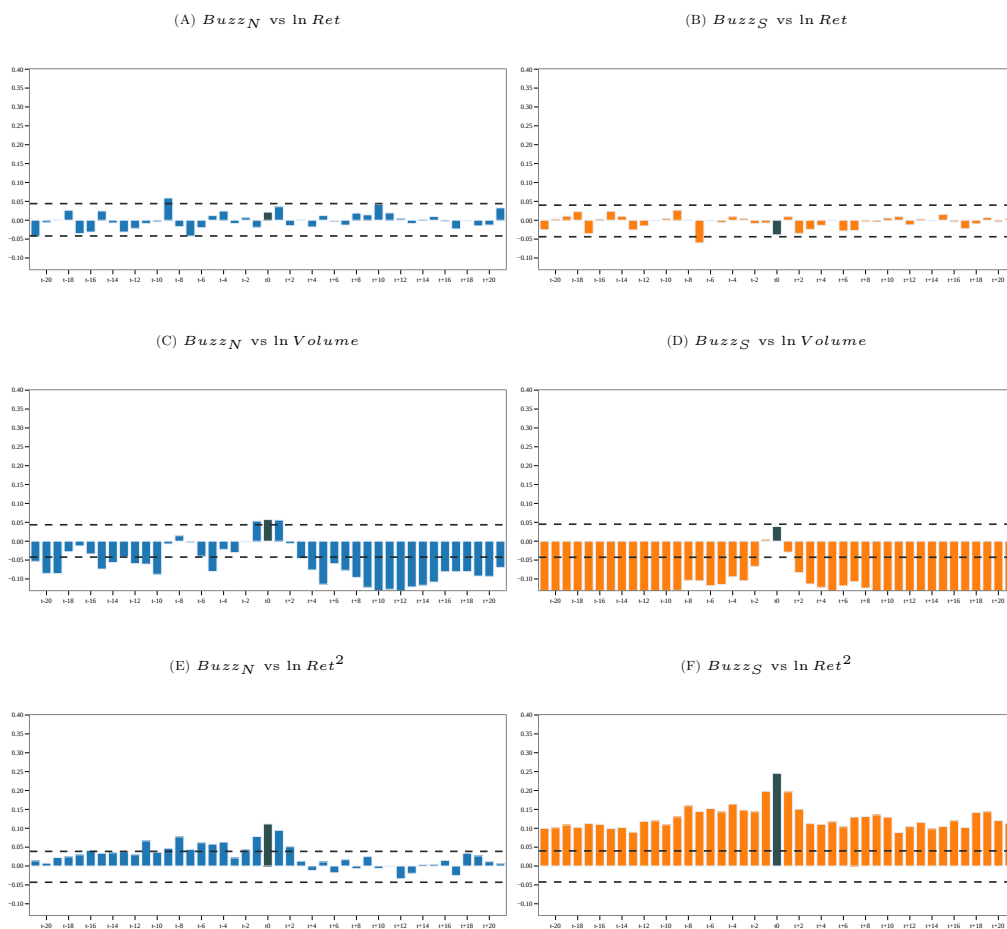
FIGURE 2.20: **Visual representation of RMEA with market variables.** This figure compares the level of ESG related media attention from news and social media for a single salient firm, Apple Inc. Panel (A) plots the time series of $Buzz_N$ (blue) and $Buzz_S$ (orange), Panel (B) plots the time series of $Sent_N$ and $Sent_S$, and Panels (C) to (D) plot market variables, in return, trading volume, and realised volatility respectively. Realised volatility is computed as the squared log returns. Sample period is from 01-Jan-2016 to 31-Dec-2021.



We observe periods where increased levels of ESG media activity corresponds with increased market activity for AAPL. Specifically, the time periods of 2016, mid to late 2018, January of 2019, and mid 2021 are highlighted as particular periods of interest. To probe whether there is predictive power, we perform cross-correlations of the $Buzz$ and $Sent$ series (Figures 2.21 and 2.22 respectively) with each of the market variables for news (LHS) and social media (RHS). When performing the correlations, we hold the market variable constant at t_0 and shift the sentiment variables in the range $t - 21$ to $t + 21$ to capture any lead-lag effects. Confidence bands at 95%

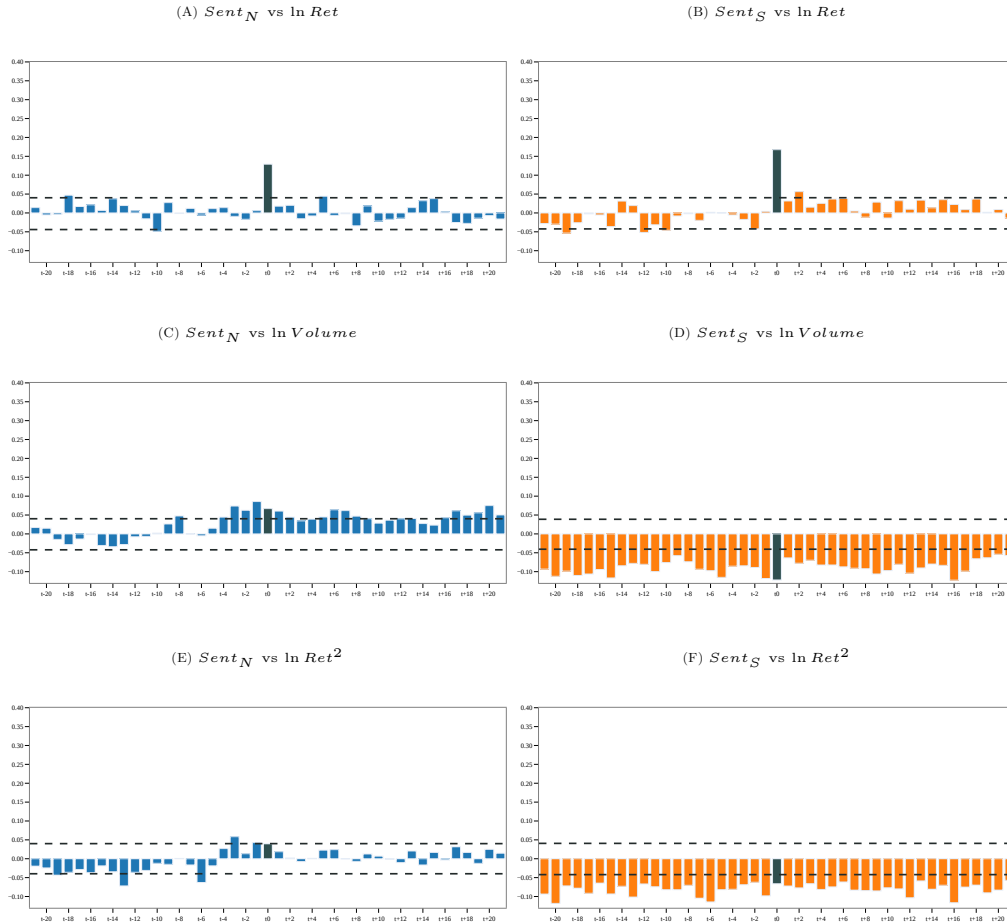
were constructed by performing bootstrap simulation using the full sample without replacement, and repeated 1000 times.

FIGURE 2.21: **Lead-lag effects of *Buzz* with key market variables for Apple Inc.** This figure presents the cross correlation of *Buzz* with key market variables: Log Return (top panel), Log Trading Volume (middle panel), and Log Realised Volatility (bottom panel) for a single salient company. Cross-correlation is calculated as the Pearson correlation of the contemporaneous daily *Buzz* variable at time t with lagged and leading market variables up to 21 days. The daily *Buzz* variable is reconstructed from 1-minute observations between the window 09:35 on day t and 09:25 on day $t + 1$. Observations in the 5-minutes following (preceeding) the open are excluded to avoid the volatility impacts associated with the market open. The measure for realised volatility is calculated as squared returns. The three panels on the left represent the cross-correlation of *Buzz* generated from news media, whilst the panels on the right represent the cross correlation of *Buzz* generated from social media. t_0 is denoted as the grey bar. Confidence bands at 95% were constructed by performing bootstrap simulation using all data in the sample (without replacement) and repeated 1,000 times. Sampling period: 01-Jan-2016 to 31-Dec-2016, excluding weekends and public holidays.



We are surprised not to find meaningful effect between stock returns and our *Buzz* variables for both news and social media, particularly given the burgeoning research that finds evidence of the influence of ESG news on stock returns (see Flammer, 2013; Capelle-Blancard and Petit, 2019; Serafeim and Yoon, 2022) as well as other studies that link social media with price impact (Yang et al., 2025). In the *Sent* variable, the relationship is significant only for the contemporaneous

FIGURE 2.22: **Lead-lag effects of *Sent* with key market variables for Apple Inc.** This figure presents the cross-correlation of *Sent* with key market variables: Log Return (top panel), Log Trading Volume (middle panel), and Log Realised Volatility (bottom panel) for a single salient company. Cross-correlation is calculated as the Pearson correlation of the contemporaneous daily *Sent* variable at time t with lagged and leading market variables up to 21 days. The daily *Sent* variable is reconstructed from 1-minute observations between the window 09:35 on day t and 09:25 on day $t + 1$. Observations in the 5-minutes following (preceeding) the open are excluded to avoid the volatility impacts associated with the market open. The measure for realised volatility is calculated as squared returns. The three panels on the left represent the cross-correlation of *Sent* generated from news media, whilst the panels on the right represent the cross correlation of *Sent* generated from social media. t_0 is denoted as the grey bar. Confidence bands at 95% were constructed by performing bootstrap simulation using all data in the sample (without replacement) and repeated 1,000 times. Sampling period: 01-Jan-2016 to 31-Dec-2016, excluding weekends and public holidays.



term with correlation of 0.13 in news media and 0.17 in social media. For both the *Buzz* and *Sent* variables, there appear to be a persistence in the relationships between $\ln Volume$ and $\ln Ret^2$ for social media, whilst in news media there is some evidence that $Buzz_N$ may be a significant predictor of $\ln Ret^2$.

2.5 ESG sentiment vs traditional measures

One of the key questions this research attempts to answer is how ESG sentiment contrasts with traditional measures of ESG, and how they might be used to compliment existing uses of traditional scores for investment decision making. Traditional measures of ESG have come under fire recently for the low rates of convergence between ESG ratings providers, leading to concerns that disagreement may adversely affect asset prices and / or decision making by investors and corporate managers (see Chatterji et al., 2016; Berg et al., 2022; Serafeim and Yoon, 2022). Moreover the qualitative, infrequent and backward looking nature with which ESG performance is measured means that traditional measures of ESG are updated at very low frequencies and causes one to question whether higher frequency measures of ESG can improve the informational efficiency of a firms ESG performance.

To answer the question of how ESG sentiment compares traditional measures, we compare our ESG sentiment measures with a popular traditional ESG rating provided by MSCI. MSCI ESG ratings are widely used throughout industry and academia, and are generally considered to be the preeminent provider of ESG ratings (see Eccles et al., 2020; Berg et al., 2022; Pástor et al., 2022). MSCI generates its ratings from a range of internal and external sources including internal questionnaires, corporate disclosures, government documents and news media. Assessments are carried out by analysts, although increasingly they have started to incorporate AI and NLP techniques into its methodology, in part to increase the frequency with which assessments can be updated. Despite this though, once a qualitative assessment has been made, it generally will not be reviewed until the following year unless an adverse ESG event motivates a review. Importantly, the ratings provided by MSCI are a measure of the firm’s financial exposure to ESG risk (both positive and negative), as opposed to actions taken by the firm that may improve (or detract) from ESG performance.

One of our first steps was to make the two very different measures of ESG comparable by aligning the frequency of the datasets to prepare for empirical analysis. We compute daily ESG composite scores $Sent_{ESG,t}$ and $Buzz_{ESG,t}$ following the procedure in Section 2.3 (Eqns 2.1 to 2.6), then apply exponential smoothing to the daily sentiment series which allows us to reduce noise in the signal without information loss. The exponential weighted average is calculated over the prior 365 days (inclusive of the current day) with a weighting parameter that assumes a half-life (h) of 90 days. The selection of h is taken as an appropriate trade off between recency and volatility. The procedure is outlined below where for brevity, we exclude the company and

media subscripts:

$$Sent_{ESG,t}^* = \frac{\sum_{n=0}^N \lambda_n \times Sent_{ESG,N-n} \times Buzz_{ESG,N-n}}{\sum_{n=0}^N \lambda_n \times Buzz_{ESG,N-n}}, \quad (2.8)$$

$$\lambda_n = (1 - \alpha)^n \quad (2.9)$$

$$\alpha = 1 - \exp \frac{\log(0.5)}{h} \quad (2.10)$$

where $Sent_{ESG,t}^*$ refers to the exponentially smoothed sentiment variable, λ_n are the weights attributed to $Sent_{ESG,m}$ for the prior $M=365$ days, and α is the rate of decay.

Next, obtain the equivalent measure from MSCI ESG ratings, our traditional proxy. So that the sentiment and traditional measures are comparable, we use the industry non-adjusted pillar scores (P_{score}) and weights (P_{weight}) to compute stock-level composite ESG scores. Again for brevity we exclude the company subscripts:

$$MSCI_{ESG,m} = \sum_{P \in pillar} \gamma_m^P MSCI_m^P \quad (2.11)$$

where $MSCI_m^P$ are the scores for pillar P at the beginning of each month m and γ_m^P are the pillar weights. By applying these transformations, the sentiment series ranges between -1 and 1, whilst the MSCI scores range between 0 and 10. To ensure they are on the same scale, we rescale $Sent_{ESG,t}^*$ to match MSCI by applying the min-max scaling algorithm:

$$Sent_{t,k,j} = a + \frac{(x - minval) \times (b - a)}{maxval - minval} \quad (2.12)$$

where $a = 0$ and $b = 10$ is the range to rescale the series to, and $minval = -1$ and $maxval = 1$ is the range the sentiment series takes. Finally, values of $Sent_{ESG,t}^*$ are taken at beginning of the month to match the frequency of MSCI.

In what follows, we demonstrate that the RMEA sentiment score is fundamentally different to our traditional proxy, MSCI. Figure 2.23 plots a scatterplot of the MSCI scores (x-axis) and the RMEA sentiment scores (y-axis) as at December 2021. If the scores were similar in their scale, we would expect to see a linear relationship, however do not see this.

Figure 2.24 illustrates the time series evolution of the sentiment and MSCI scores for four representative companies: Apple Inc., Pfizer Inc., Walmart Inc., and Exxon Mobile Corp. Whilst we can see obvious divergences between each of the series, from the graphs alone it is not clear whether there are any meaningful relationships between the three series.

FIGURE 2.23: **Point in time comparison of RMEA with Traditional ESG.** This figure compares the exponentially smoothed daily composite sentiment signals with the traditional ESG proxy (MSCI) as at December 2021 for news (Panel (A)) and social media (Panel (B)).

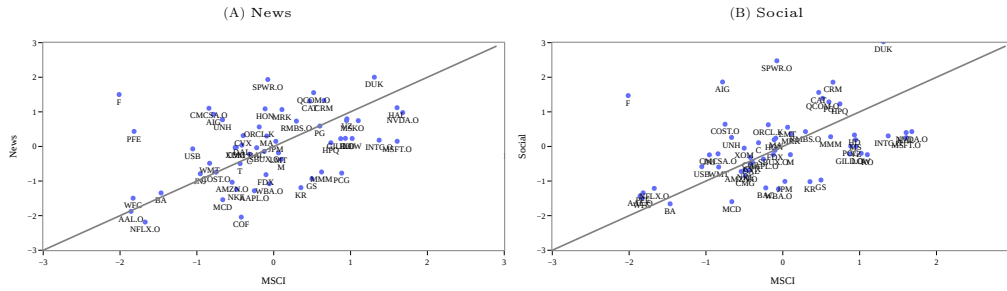
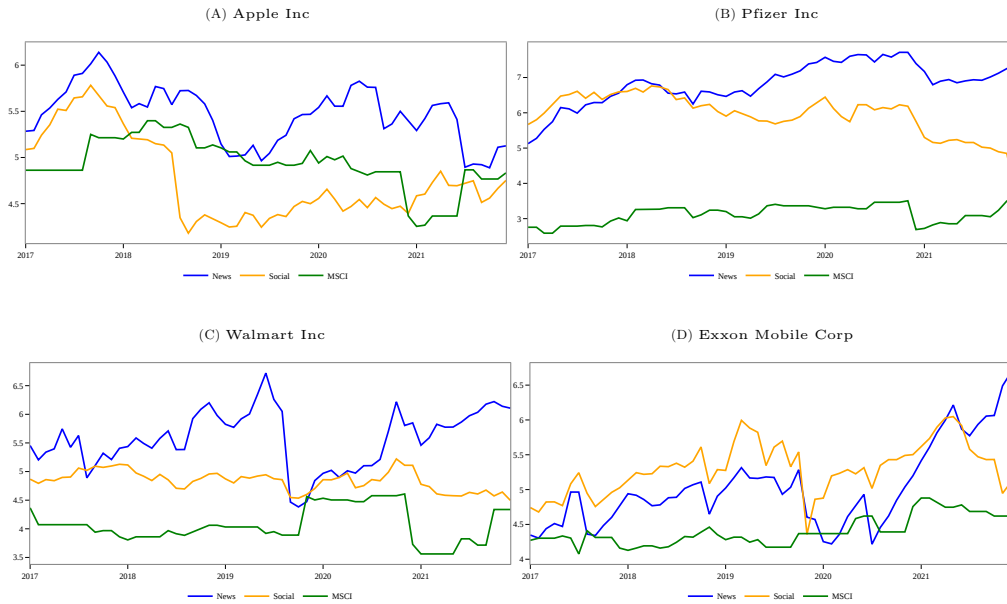


FIGURE 2.24: **RMEA vs Traditional ESG.** This figure compares the exponentially smoothed daily composite sentiment signals for news and social media with the traditional ESG proxy (MSCI) presented here at a monthly frequency. The exponential weights for the sentiment series are based on a rolling 365 day lookback period with a half-life of 90 days. The sample period is from 01-Jan-2016 to 31-Dec-2021.



Next, we test the hypothesis that $MSCI$, $Sent_N^*$ and $Sent_S^*$ are drawn from the same distribution by performing the Kruskal-Wallis and Friedman tests on the standard deviations of the series on both the full sample, and for each year in the sample. The Kruskal-Wallis test is the non-parametric form of the one way ANOVA, with the null that the medians of the groups are equal. The Friedman test is analogous to the one way repeated measures ANOVA. Crucially both tests do not require the assumption of normality. Table 2.4 presents the results. We see that in almost all cases that we are able to reject the null hypothesis and determine that the series are not similar. The only exception is where we fail to reject the null between $Sent_N$ and $Sent_S$ in the year 2020.

TABLE 2.4: **Similarity tests.** We use the non-parametric forms of Analysis of Variance (ANOVA) to test whether $MSCI$, $Sent_N$, and $Sent_S$ composite ESG scores originate from the same distribution. Columns (1) to (3) present the results of pairwise tests (test statistic and level of significance below) using the Kruskal-Wallis test. Column (4) present the results for the Friedman tests. Scores were ranked on the standard deviation of scores for each of the sample companies during the respective time periods (all, 2017, 2018, 2019, 2020 and 2021). ***, **, and * indicates significance at 1%, 5%, and 10% respectively.

	Pairwise			Friedman
	MSCI v News (1)	MSCI v Social (2)	News v Social (3)	MSCI v News v Social (4)
all	38.79 ***	13.73 ***	8.79 ***	33.24 ***
2017	54.66 ***	26.37 ***	8.96 ***	42.66 ***
2018	39.21 ***	8.96 ***	8.76 ***	34.86 ***
2019	46.73 ***	16.25 ***	13.40 ***	37.66 ***
2020	35.83 ***	26.14 ***	2.36	40.79 ***
2021	38.79 ***	18.93 ***	5.85 **	25.55 ***

Finally, Figure 2.25 presents the 12 month rolling correlation between $MSCI$ and $Sent_N^*$, $MSCI$ and $Sent_S^*$, and $Sent_N^*$ and $Sent_S^*$. It is easy to see that despite statistical differences in the sample deviations between $Sent_N^*$ and $Sent_S^*$ that the series are closely correlated for our representative stocks. This does raise some interesting questions as to how closely ESG sentiment from news and social media are aligned, or whether there are informational advantages to using one series over the other. We leave an in-depth analysis of the dynamic between $Sent_N^*$ and $Sent_S^*$ as a topic for future research.

2.6 Conclusion

This study contributes to the evolving discourse on ESG measurement by shedding light on the dynamic role that public opinion can play in ESG analysis. Importantly, it challenges the notion of an ESG metric and paves the way for integrating sentiment-driven approaches in sustainable finance. We also add to the behavioural finance literature by dissecting sentiment into distinct groups of discussion and media type. Crucially it shows that not all sentiment is equal. In particular, we explore a novel ESG dataset with significant potential for stock-level analysis and its impact on asset pricing. The dataset, provided by Refinitiv Marketpsych ESG Analytics (RMEA), differs from traditional measures of ESG performance such as MSCI ESG Ratings, in that it is based purely on the sentiment and attention of public opinion of a company's ESG

FIGURE 2.25: **Rolling correlation between sentiment and Traditional ESG.** The sample period is from 01-Jan-2016 to 31-Dec-2021.



activities.

The RMEA database has three key advantages over traditional measures: 1) it is independent of company influence, reducing the risk of biased reporting or greenwashing; 2) it minimises subjectivity in the assessment process by relying on automated processes; and 3) due to automated data collection and analysis, the RMEA scores are available at higher frequencies allowing for unique insights to be gained, that would otherwise be missed using lower frequency measures. From a practical perspective, these advantages make RMEA particularly useful for investors, asset managers, and policymakers seeking dynamic ESG insights that go beyond periodic company disclosures and annual ESG scores. For example, policymakers may use dynamic ESG to monitor corporate announcements against its public perception. Alternatively, investors may be alerted to changes in a company’s sustainability profile long before it is captured by traditional ESG measures. In essence, dynamic ESG has the potential to enhance risk management, inform investment decisions and complement qualitative ESG frameworks by providing a more timely reflection of ESG performance.

Our analysis yields some interesting insights. It is encouraging to see similarities in trends between the sentiment signals and the traditional ESG measure, however despite this, our analysis reveals informational differences between the two ESG measures. This is a critical point when advocating the inclusion of an alternative signal in investment processes. We also find im-

portant distinctions in the information channels used by investors to discuss ESG, highlighting the importance of disseminating sentiment by media source to enrich analysis. Our research also reveals a deviation in the stylised facts of sentiment from behaviours expected in the behavioural finance literature suggesting there is a uniqueness to ESG-sentiment not captured in general sentiment.

This research opens the door for further analysis. Future analysis could contrast ESG sentiment against sentiment more broadly to better understand drivers that differentiate varying types of sentiment. Future research could consider other sentiment proxies that expand the dataset's coverage and could explore the predictive power of ESG sentiment for asset pricing and financial performance in greater depth. Investigating how sentiment-based ESG scores complement ESG ratings could provide further insights into how quickly ESG-related information is reflected in market prices. Additionally, examining the role of sentiment measures in different asset classes, such as fixed income and private markets, could further validate their broader applicability.

Chapter 3

ESG sentiment and stock price volatility

3.1 Introduction

Numerous studies dissect the impact of environmental, social, and governance (ESG) investing on asset returns and performance (see Friede et al., 2015; Whelan et al., 2021; Atz et al., 2023, for a comprehensive summary), however less attention has been paid to its impact on volatility. Yet volatility is crucial not only in our understanding of asset price behaviour (Corsi, 2009; Patton and Sheppard, 2015), but also for risk management (Engle, 2004). As sustainability and investing increasingly become intertwined, understanding the volatility dynamics following ESG information events, including a change in ESG sentiment, will become necessary for financial institutions and asset managers, for example, when managing risk using volatility-based Value-at-Risk (VaR) levels, and modelling the variability of ESG-integrated portfolios over time (Sabbaghi, 2022). Given the growing integration of ESG considerations in investment strategies, the focus on volatility forecasting is highly relevant.

This research investigates the predictive power of ESG sentiment and attention measures on stock price volatility. In particular, we focus on the volatility of the sentiment variable to proxy uncertainty in ESG. To date, much of the research that identifies ESG's contribution to risk centres on investor uncertainty regarding a company's ESG profile, reflected in ESG ratings disagreement between providers (Brandon et al., 2021; Avramov et al., 2022). Although this approach incorporates various expert opinions, ESG ratings do not update frequently and are

not reflective of current events. In contrast, sentiment signals the direction of public opinion, and by leveraging the wisdom of the crowd, can provide an almost real-time indication of whether a company's activities relating to environmental, social, or governance concerns are perceived positively or negatively. By focusing on the volatility of ESG-sentiment we associate disagreement in the public discourse with uncertainty and expand the definition of ESG uncertainty to include alternative measures.

Our sentiment measures are obtained utilising a large commercial dataset of stock-level ESG sentiment and attention measures derived from news and social media sources. There are a number of important features of this dataset that we exploit in our study and that motivate in part, our research questions. First, the use of 1-minute frequency ESG sentiment and attention data adds granularity and precision, a significant methodological strength. This is one of the most important features of our dataset due to the low persistence of sentiment on stock price dynamics (see Sun et al., 2016; Gan et al., 2019). Our main results are obtained from considering overnight sentiment only. Second, differentiating sentiment from news and social media sources allows independent study of these two very important mediums of information dissemination. This approach offers a novel perspective on their informational content and underscores the increasing impact of social media as a prominent information channel. Finally, the ability to decompose sentiment into the three environmental, social, and governance pillars, enables us to understand how sentiment relating to different types of issues can impact volatility. Therefore, we aim to answer the following three questions: 1) Does ESG sentiment influence stock price volatility; 2) which media format is most relevant in explaining and predicting volatility; 3) which of the environmental, social or governance pillars of ESG has the most impact on volatility?

Audrino et al. (2020) lays the groundwork for this study by demonstrating that sentiment and attention variables are significant predictors of stock price volatility. This study follows their framework by utilising the heterogeneous autoregressive (HAR) model of Corsi (2009), extended to include sentiment and attention variables within an ESG context. In Panel-HAR regressions we find that a one standard deviation increase in the volatility of sentiment leads to an increase in stock price volatility between 0.7% and 1.73% that are both economically and statistically significant. Media attention reveals an even greater impact to volatility of between 3.96% and 8.12%. However, sentiment yielded counter-intuitive results when examining sentiment on social issues, suggesting that positive sentiment in the social pillar leads increased volatility. One possible explanation is that the ambiguous nature of social issues causes investors to perceive activities in this area as being costly with uncertain future benefits.

In individual regressions and one-day ahead forecasts, we find that when the sentiment and attention variables are considered collectively, social media had a greater influence than news media in explaining and predicting volatility. Similarly, when decomposing sentiment into its pillar groups, the social pillar was more influential on volatility than the environmental and governance pillars. These findings are inconsistent when considering the ESG uncertainty measure in isolation, suggesting that media attention is a driving force behind stock price volatility. Finally, contrary to literature that suggest the separation of environmental, social, and governance data for analysis, we obtained better out of sample forecasts when the information signals were combined into a single measure.

Our study differs from Audrino et al. (2020) in that we focus on the decomposition of sentiment and media attention into their ESG pillars, and aggregate high-frequency sentiment observations during the overnight period. In this way we add to the literature on volatility forecasting by incorporating ESG sentiment variables and demonstrate that overnight sentiment is sufficient to improve volatility forecasts. Additionally, we contribute to the ESG literature on materiality by providing insight into what the public deems to be material and demonstrating its impact on stock return volatility. It remains an open question whether materiality from a public perspective aligns with the SASB classification of financial materiality which is the benchmark determinant of materiality for investors. Third, unlike other studies that attempt to forecast volatility using ESG news (Guo et al., 2020; Sabbaghi, 2022), we exploit the segregation of ESG media activity by media source, to demonstrate differences in outcome depending on whether the source of media activity is from news or social media. To the best of our knowledge, we are one of the first to contrast the effects of news media from that of social media on stock-return volatility, implying that the informational content on the two media types differs in their impact on volatility.

This chapter is structured as follows: the next section describes the related literature and motivation for performing this analysis, Section 3.3 describes the sample construction and data used in our analysis, including a detailed description of the Refinitiv Marketpsych ESG analytics (RMEA) dataset. Section 3.5 investigates the explanatory power of the ESG sentiment and attention variables on realised stock price volatility in a panel-HAR setting whilst Section 3.6 investigates their predictive power on individual stocks. Section 3.7 discusses the findings, and finally, Section 3.8 concludes.

3.2 Related literature and motivation

This research is related to literature that examines the relationship between ESG factors and risk, and combines with the behavioural finance literature that studies sentiment's influence on realised volatility. Crucially, it examines the evolution of risk with the widespread adoption of ESG in investment decision-making, and the contribution that sentiment can make in this evolution.

Investing along sustainability guidelines and social capital have long been associated with improved risk management. Theoretical concepts such as instrumental stakeholder theory (Donaldson and Preston, 1995; Jones, 1995), the insurance hypothesis (Godfrey, 2005; Godfrey et al., 2009), and risk reduction hypothesis (Jo and Na, 2012), suggest that a build up of social capital and increased stakeholder engagement can mitigate negative effects of an environmental, social or governance crisis. Similarly, empirical analysis links high ESG performance negatively with indicators of risk, such as lower cost of capital (Hong and Kacperczyk, 2009; El Ghouli et al., 2011; Baker et al., 2022; Seltzer et al., 2022; Newton et al., 2024), lower stock price volatility (Eccles et al., 2014; De and Clayman, 2015), and reduced exposure to downside risk (Lööf et al., 2022; Hoepner et al., 2024; Yang et al., 2024). Several studies also associate high ESG performance with improved risk-adjusted returns (Kumar et al., 2016; Verheyden et al., 2016; Giese et al., 2019a,b). More recently, studies examining the effect of adverse news on stock price returns find that a high ESG profile can dampen market price reaction (Flammer, 2013; Capelle-Blancard and Petit, 2019).

Emerging research however, reveals that uncertainty in ESG may now be contributing to risk. Widespread adoption of ESG, and lack of uniform definitions have encouraged competing and contradictory signals of ESG performance that cause confusion for investors (Chatterji et al., 2016; Kotsantonis and Serafeim, 2019; Berg et al., 2022). In this environment, Avramov et al. (2022), posits that when investors are uncertain of a company's ESG profile, equities are perceived to be riskier in equilibrium and overall demand for equities decreases. Investigating the effect of ratings disagreement on stock prices, Brandon et al. (2021), find that investors demand a higher risk premium for companies with high ratings disagreement between providers. Meanwhile, using a measure of ESG risk that accounts for the entropy in ESG scores, Capelli et al. (2021), find that cross-sectional dispersion of ESG scores improve the predictive power of volatility models when combined with financial risk measures.

We contribute to this literature by considering an alternative measure of ESG uncertainty:

Dispersion in ESG sentiment. Much of the analysis to date relies upon ESG ratings, however there are several advantages to using sentiment data. For example, ESG ratings are slow to update and often reviewed only annually. Sentiment data on the other hand, are available at much higher frequencies, such as at 1-minute intervals, providing a timely measure of ESG uncertainty. Additionally, the sentiment we use in this analysis is derived from news and social media, providing a perspective of ESG that is not curated, and is independent from company influence. Finally, much of the literature associating sustainable investing with improved risk management refers to intangible measures such as “trust”, “moral capital” and “reputation”. However these are often excluded from consideration in the ESG ratings formulation. This is despite being reflective of long term shareholder value (Edmans, 2023). With the advent of Natural Language Processing (NLP), these intangible measures can be extracted from news articles and social media posts to be reflected as sentiment. Therefore, by considering disagreement in sentiment as a measure of ESG uncertainty, we address a gap in the literature, and expand the definition of ESG uncertainty to include alternative measures.

This research also relates to the behavioural finance literature that examines the relationship of sentiment with stock price volatility. Much of the literature finds sentiment and search volumes are useful predictors of stock price volatility (see Antweiler and Frank, 2004; Wang et al., 2006; Ho et al., 2013; Andrei and Hasler, 2015; Hamid and Heiden, 2015; Dimpfl and Jank, 2016; Caporin and Poli, 2017; Behrendt and Schmidt, 2018; Gan et al., 2020), however, analysis that focuses explicitly on ESG sentiment is in its infancy. Moreover, the literature that examines the impact of ESG news and the related price reaction provides an important link between ESG sentiment and a company’s risk profile. Still, it is not yet understood how ESG-related media activity impacts on stock price volatility, nor whether they have any predictive power in forecasting future volatility. As investing along ESG grounds becomes normalised, understanding ESG volatility dynamics and integrating ESG measures into volatility forecasts and models will be crucial. Banks and other financial institutions, for example, may need to consider adding ESG measures into Value at Risk (VaR) models for ESG-integrated portfolios (Cappelle-Blancard and Petit, 2019; Sabbaghi, 2022), whilst understanding time-varying dynamics will be important when modelling the variability of ESG-integrated portfolios over time (Sabbaghi, 2022).

Therefore, our first hypothesis tests whether ESG sentiment variables, mainly volatility in sentiment and level of media attention, are useful predictors of stock price volatility.

***H1a:** An increase in the realised volatility of ESG sentiment (RV_{Sent}) is associated with an increase in stock price volatility,*

***H1b:** An increase in ESG media attention ($\ln Buzz$) is associated with an increase in stock price volatility,*

An important question related to this is whether ESG sentiment derived from social media has the same impact as sentiment derived from news media. For example, much of the research to date focuses on the impact of news media, yet a recent study by Gan et al. (2020) shows that since 2016, social media has overtaken news media to be the dominant medium for information dissemination. It is, therefore, critical in our understanding of volatility to identify how sentiment measures derived from social media differ from those derived from news media.

***H2a:** An increase in the realised volatility of ESG sentiment from news or social media is associated with an increase in stock price volatility,*

***H2b:** ESG media activity from social media has greater explainable and forecasting power than from news media,*

A separate literature argues for the decoupling of E, S, and G components in ESG analysis due to ESG being a multi-dimensional construct comprising of distinct E, S and G factors (Li and Wu, 2020). This view is based on stakeholder management theory (Freeman, 1984; Donaldson and Preston, 1995), and that the E, S and G components are relevant to different stakeholders in different ways and that individual performances in themselves have a direct relationship with idiosyncratic risk (Malshe et al., 2023). Whilst the literature examining this is mixed, it leans towards the environmental pillar, for example, through increased disclosures, having a significant and negative impact on idiosyncratic risk (Sassen et al., 2016; Benlemlih et al., 2018; Izcan and Bektas, 2022). We take the complementary view that uncertainty relating to the environmental pillar will have a significant and positive impact on idiosyncratic risk. This leads to our final hypothesis:

***H3a:** An increase in the realised volatility of E, S, or G sentiment is associated with an increase in stock price volatility,*

***H3b:** Uncertainty in the environmental pillar has a greater impact on stock price volatility than from the social or governance pillar.*

3.3 Data

The sample consists of 45 US companies. Using a quota sampling method, five companies are selected from each of the nine Refinitiv TRBC Economic Sector Groups: Basic Materials, Consumer Cyclical, Consumer Non-cyclical, Energy, Financial, Healthcare, Industrial, Technology, and Utilities. The Real Estate sector is excluded from the analysis due to insufficient data. Companies are first screened by market capitalisation and media coverage, then assessed for data consistency over the sample period. Companies exhibiting abnormal media attention—defined as more than two standard deviations above their average in any month-year—are excluded. From the remaining universe, the five companies with the highest media attention in each sector are selected. The sample period starts from 1-Jan-2016 and concludes on 31-December-2021. Table A.2.2 in Appendix A.2 presents a sector representation of stocks in our sample.

Our choice of sampling methodology is motivated in two ways. First, that future realised volatility may be influenced differently by sentiment and attention variables depending on the specific stock under consideration. Second, the materiality of environmental, social and governance concerns may vary depending on the sector to which the company belongs to. For example, according to the materiality finder by what was formerly the Sustainability Accounting Standards Board (SASB), environmental concerns are identified as being financially material to the Mining and Materials sector, whereas social concerns are more relevant to the Financial sector.¹ In these cases, we expect attention and sentiment related to environmental concern to have a greater influence on future realised volatility for companies in the Materials sector, more so, for example than the Financial sector.

In what follows, we describe the data and variables used in our analysis. Despite observations in our raw datasets being available at high frequencies, our predictive regression models are based on daily data. The aggregation techniques that we use for each dataset are outlined below.

3.3.1 Realised Volatility

The 5-minute intraday price summaries for the 45 stocks in the sample are obtained from LSEG Tick History (formerly Thomson Reuters Tick History - TRTH). Constructing realised volatility measures from intraday returns at a 5-minute frequency is well established in the literature since these display greater dynamics and conform well to the long memory property of stock return

¹<https://sasb.ifrs.org/standards/materiality-finder/>.

volatility (see Andersen et al., 2001; Behrendt and Schmidt, 2018).²

We cleanse the data following the procedure suggested by Barndorff-Nielsen et al. (2009), and modified to suit the intraday summary data.³ Specifically, we delete observations that (1) fall outside of the regular trading hours from 09:30 to 16:00 EST, (2) have bid, ask or last price equal to zero, or (3) have a last price above (below) the ask plus (bid minus) the bid-ask spread. Next we adjust the last price for corporate actions such as stock splits and consolidations that may have occurred during our sample period. The continuously compounded 5-minute return series are computed as the logarithmic difference between prices at the 5-minute interval.

We follow the method of Andersen et al. (2001) to compute the realised volatility estimator as the sum of squares of returns, demeaned and filtered by an MA(1) process. We use this estimator to balance simplicity with the elimination of negative serial correlation in high-frequency returns induced by non-synchronicity of observed prices and the inherent bid-ask spread. The MA(1) model is estimated for each of the 5-minute return series using the full sample of data. On the rare occasion where no trading has been recorded during a trading day for a stock (such as for public holidays, or trading halt), we fill missing values with the previous day's volatility. In doing so, we impose that in the absence of trading activity, the volatility of the previous day is the best estimate of what volatility would have been on that day.

3.3.2 ESG sentiment and attention measures

We obtain measures of ESG sentiment and media activity from Refinitiv Marketpsych ESG Analytics (RMEA), a commercial database that utilises Machine Learning (ML) and a state-of-the-art Natural Language Processing (NLP) engine to extract sentiment from news articles and social media posts. The novelty in this dataset is its exclusive focus on the sentiment relating to public discourse on environmental, social, and governance topics. Another important feature of this dataset is the availability of observations at 1-minute frequencies. This differs from traditional measures of ESG performance that typically update only annually. Not only does this allow for a timely representation of ESG, but also facilitates deeper analysis of the influence that ESG has on price dynamics.

The RMEA database covers more than 30,000 companies across 252 countries, and from January 2021, included news sources from twelve languages in addition to English.⁴ Content for

²Additionally, in a study comparing over 400 different realised variance estimators, Liu et al. (2015) find no significant benefit when deviating from a 5-minute sampling frequency.

³In Barndorff-Nielsen et al. (2009) the procedure is applied to trade and quote data (TAQ).

⁴Until February 2020 English-language text was exclusively used after which Arabic, Chinese, Japanese and

the news feed is evaluated from reputable sources such as Reuters news, mainstream news outlets, and internet news collected by LexisNexis. The social media feed consists of content from over 2,000 social media sites collected by MarketPsych and LexisNexis. Content is also screened and classified according to perspective and outlook. Content creators who have the characteristics of ideologues, promoters, robots or spammers are removed from the feed both historically and in real time. Importantly, the RMEA database maintains a genuinely external perspective of a company’s ESG activities by excluding company related content such as press-releases, disclosure statements, and reports, that might bias sentiment in the company’s favour.

The RMEA data consists of sentiment (*ESG*, *Controversy*), and attention (*Buzz*) variables across ten ESG categories: *emissions*, *environmentalInnovation*, *resourceUse*, *community*, *humanRights*, *product*, *workforce*, *cSRStratgey*, *management*, and *shareholders*. In total, there are 29 variables to consider. The RMEA *ESG* scores capture both positive and negative sentiment relating to an ESG topic. They range between -1 and 1 and are positive in their tonality, meaning a higher score is subjectively positive. The *Controversy* scores capture only sentiment relating to ESG controversies. They range between 0 and 1 and are negative in their tonality. The *Buzz* variable is an indication of the volume and intensity regarding discussion on an ESG topic for a company. *Buzz* range between 0 and inf. In addition, the variables are available consisting of content from both news and social media sources (*News_Social*), or decomposed by media type (*News* only or *Social* only).

We start by combining the *ESG* and *Controversy* scores to form a single measure of sentiment (*Sent*). By its construction, the underlying variables that contribute negatively to the *ESG* score may also contribute to the *Controversy* score, however the reverse may not be true. Therefore, to capture the overall sentiment of a company at any point in time, it is prudent for us to merge these two variables together. The *Sent* variable is therefore constructed as the simple average of the timestamped observation of the *ESG* and negated *Controversy* for each company j , category c , media type k and timestamp i .⁵ As the *Controversy* score is negative in its tonality (i.e. a higher score is subjectively negative), it is negated to align its tonality with the *ESG* measure. For brevity, we suppress the company, category and media type subscripts:

$$Sent_i = \frac{1}{2}(-Controversy_i + ESG_i). \quad (3.1)$$

Portuguese-language news sources were added to the NLP engine. From January 2021, Dutch, French, German, Indonesian, Italian, Korean, Russian and Spanish-language sources were added.

⁵This approach is different to literature that combines the *ESG* and *Controversy* scores of a related product, Thompson Reuters Asset 4 (see Yang et al., 2024, as an example). This is primarily due to differences in how the *Controversy* scores are formulated between the two products.

Next, we combine each of the category variables for *Sent* and *Buzz* cross-sectionally to form the individual *E*, *S*, and *G* pillar scores, and the composite *ESG* score. We deviate from the methodology suggested in Refinitiv (2020) by computing the pillar scores first then aggregating to daily. This is because of the inclusion of the quadratic variation of the sentiment variable that is integral for our research. By aggregating variables at the category level first, we avoid the need to compute cross-terms when computing realised volatility at the pillar and composite level. The *Sent* scores are calculated as the *Buzz*-weighted average of the category scores belonging to the pillar group. By using a *Buzz*-weighted average, we allow the data to determine each category's relevance to the overall pillar (or composite score), based on the level of attention it receives. This approach enables dynamic adjustment of materiality, rather than relying on fixed weights. The *Buzz* scores on the other hand are calculated as the total sum of category *Buzz* in each respective pillar and composite ESG groups.

$$Buzz_{P,i} = \sum_{c \in P} Buzz_{c \in P,i}, \quad (3.2)$$

$$Sent_{P,i} = \sum_{c \in P} \omega_{c \in P,i} \times Sent_{c \in P,i}, \quad (3.3)$$

$$\omega_{c \in P,i} = \frac{Buzz_{c,i}}{\sum_{c \in P} Buzz_{c,i}}, \quad (3.4)$$

where $c \in P$ represents the category variable c belonging to pillar group P , P represents the *E*, *S*, *G* pillar, and *ESG* composite groups, and ω represents the category *Buzz*-weight.

The combined variables are then aggregated from an intraday measure to a daily frequency using a method tailored to each variable. For *Buzz* we calculate the sum and apply a logarithmic transformation, whilst for *Sent* we calculate the mean and standard deviation for each company. This aggregation occurs over a defined window which spans from market close on day t at 16:00 to five minutes before market open on day $t+1$ at 09:25, in the case of US markets. This window represents the overnight period ensuring consistency in daily data summarisation, and capturing new information that may influence asset dynamics outside the regular trading window. The overnight period was selected as it has been shown to have improved predictability in volatility models (Gan et al., 2024). Sentiment observations are excluded around market open to avoid any sentiment associated with volatility at the open.⁶

⁶In robustness checks, the same reasoning applies to sentiment observations in the 5-minutes prior to market close.

$$\ln Buzz_{t,P} = \ln \left(\sum_{i=\tau_1}^{\tau_2} Buzz_{i,P} \right), \quad (3.5)$$

$$Sent_{t,P} = \frac{1}{n} \sum_{i=\tau_1}^{\tau_2} Sent_{i,P}, \quad (3.6)$$

$$RVSent_{t,P} = \sqrt{\frac{\sum_{i=\tau_1}^{\tau_2} (Sent_{i,P} - \overline{Sent}_P)^2}{n}}, \quad (3.7)$$

where $\tau_1=16:00$ and $\tau_2=09:25$. The sum of *Buzz* provides the total level of media attention received. The logarithmic transformation is applied to the daily *Buzz* measure to reduce the skewness of the raw *Buzz* measure. The daily mean of *Sent* captures the average sentiment in the general population towards a company's E, S or G activities. *RVSent* measured as the standard deviation of *Sent*, is a measure of disagreement in sentiment and hence is our proxy for uncertainty. Table 3.1 presents the summary statistics of the ESG variables used in our analysis.

Finally, we standardise the pillar and composite ESG scores by calculating a conditional time-series z-score achieving a zero-mean, unit standard deviation over a 3-month rolling window. This approach ensures that the scores adapt to rapidly changing sentiment conditions, reflecting recent shifts in the data. Importantly, missing values are left untreated up to this point, i.e. when performing cross-sectional aggregation across categories, treating them as 'Missing Not at Random' (MNAR), to avoid artificially imposing sentiment where none is available. By not pre-filling missing values with zeros, we avoid any distortion in the aggregated sentiment scores, which would otherwise artificially lower category averages. This approach mitigates the dampening effect that data sparsity could introduce, allowing the aggregate sentiment to more accurately reflect only the categories where sentiment data is present, without imposing an undue influence from categories with missing values. As a final step, we fill forward missing values only after standardisation, preserving the integrity of the data while providing continuity in the ESG variables.

There may be concern that the sentiment, attention, or market variables may be highly correlated either with each other, leading to multicollinearity in our results. Figure 3.1 summarises the correlations of the sentiment and market variables. The correlation coefficients for news media are represented in the lower triangle, with social media represented in the upper triangle. Correlations between the variables are low, except between the attention variable ($\ln Buzz$) for the social and governance pillars in news media ($\rho=0.71$) and social media ($\rho=0.72$).

TABLE 3.1: **Summary Statistics.** This table presents the summary statistics for the sentiment and attention variables used in this analysis for News media (Panel A) and Social media (Panel B). The sample consists of 45 stocks (5 from each of the Refinitiv TRBC Economic sectors excluding Real Estate) and covers the period from 01-Jan-2016 to 31-Dec-2021. Data are obtained from Refinitiv Marketpsych ESG Analytics (RMEA) at 1-minute frequencies. Columns (1), (2), (3) present $\log Buzz$, $Sent$, and $RVSent$ for the Environmental pillar. Columns (4), (5), and (6) present the same for the Social pillar, and Columns (7), (8), and (9) represent the Governance pillar. $\log Buzz$, $Sent$ and $RVSent$ for each pillar are computed per the procedure outlined in Section 3.3.2 (Eqns 3.1 to 3.7). The window over which to aggregate 1-minute observations to daily frequency is between 16:00 t and 09:25 $t+1$. Missing values are left untreated and classified as “Missing not at random” (MNAR). All variables are conditionally standardised to be zero-mean, unit standard deviation over a 3-month rolling window, and windorised at 95% confidence to remove outliers.

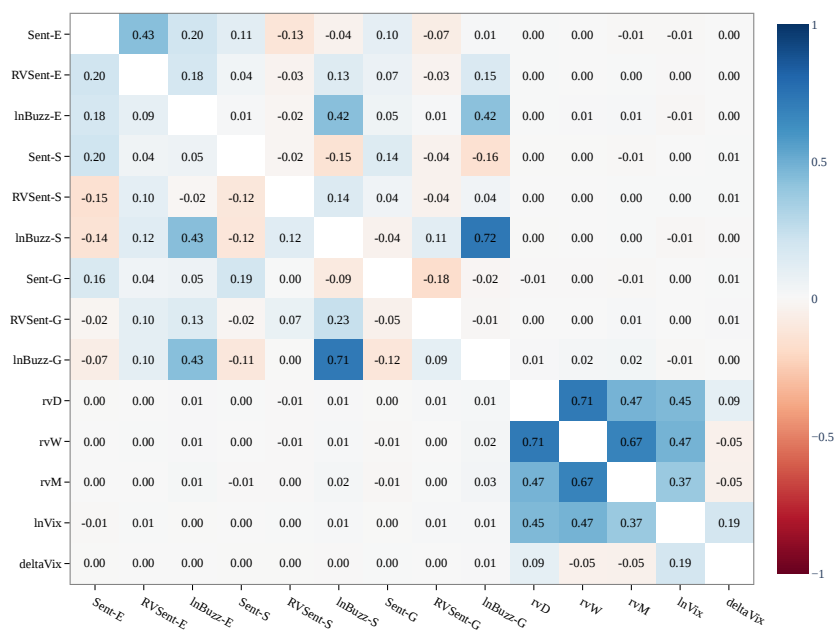
Panel A: News									
	Environment			Social			Governance		
	$\log Buzz$	$Sent$	$RVSent$	$\log Buzz$	$Sent$	$RVSent$	$\log Buzz$	$Sent$	$RVSent$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
count	40,455	57,828	51,651	55,953	57,828	51,651	39,325	57,828	51,651
mean	2.50	0.17	0.30	3.54	0.11	0.66	1.96	-0.02	0.32
std	1.61	0.32	0.24	1.78	0.48	0.27	1.41	0.26	0.24
min	-0.69	-1.00	0.00	-0.69	-1.00	0.00	-0.69	-1.00	0.00
25%	1.39	0.00	0.00	2.30	-0.21	0.55	0.69	-0.08	0.00
50%	2.40	0.05	0.33	3.47	0.09	0.71	1.79	0.00	0.36
75%	3.60	0.27	0.49	4.71	0.43	0.83	2.94	0.02	0.49
max	9.05	1.00	1.41	9.75	1.00	1.41	8.53	1.00	1.41
Panel B: Social									
	Environment			Social			Governance		
	$\log Buzz$	$Sent$	$RVSent$	$\log Buzz$	$Sent$	$RVSent$	$\log Buzz$	$Sent$	$RVSent$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
count	29,871	62,116	55,237	60,305	62,116	55,237	43,838	62,116	55,237
mean	1.68	0.07	0.19	2.88	-0.03	0.76	1.47	-0.06	0.34
std	1.45	0.21	0.22	1.52	0.46	0.26	1.17	0.23	0.24
min	-0.69	-1.00	0.00	-0.69	-1.00	0.00	-0.69	-1.00	0.00
25%	0.69	0.00	0.00	1.79	-0.31	0.69	0.69	-0.13	0.17
50%	1.39	0.00	0.12	2.89	-0.04	0.81	1.39	0.00	0.38
75%	2.56	0.07	0.36	3.86	0.20	0.89	2.20	0.00	0.50
max	7.97	1.00	1.41	9.24	1.00	1.41	7.53	1.00	1.41

To address potential multicollinearity between the sentiment and control variables, variance inflation factors (VIF) are computed and presented in Table 3.2. The computed values are low and below the threshold of 5, indicating that multicollinearity is not a concern.

3.3.2.1 Informational content in news and social media

It is an open question whether ESG sentiment derived from news and social media differ in the information they provide. If the attention and sentiment measures are informationally similar across both the media sources and ESG pillar groups, our investigation may be considered a specific case of Audrino et al. (2020), and unlikely to produce the novel insights this research aims to achieve. Whilst there is some evidence to suggest that the information in social media is of a different nature to news media (Audrino et al., 2020; Gan et al., 2020), it has not been tested from an ESG perspective. Similarly, while Chapter 2 demonstrates statistical differences

FIGURE 3.1: **Correlation of sentiment and market variables.** News (social) media is represented on the lower (upper) triangle.



in ESG sentiment from news and social media using pairwise tests, it was not extended to the pillar groups.

One way to test the similarity of our variables is to examine the occurrences of extreme sentiment and compare across media types and pillars. We do this in two ways. First, we examine the degree to which news and social media differ across each of the E, S and G pillars, and second, we examine the degree of similarity between the pillar groups for news and social media separately. We define days of extreme sentiment as days with high *Buzz* generation and a sentiment value at or around ± 1 . On these days, we posit that conviction of sentiment is strongest and validated by a large number of contributors. On days where sentiment is weak (i.e. with a value at or around 0), this may imply one of two things. Either contributors were indifferent to the event, thereby eliciting a neutral response, or that there was such disagreement amongst contributors that the signal becomes little more than noise.

We start by examining the differences between the E, S and G pillars (P) for news and social media. For each media type, we interact the $\ln Buzz_P$ and $Sent_P$ variables and sort from highest to lowest to form a measure of "extremeness" for each company. Extreme days are identified as those days falling in the top or bottom 10% of the ranked extremeness measure. We then compare the coincidence of these days occurring at the same time. The coincidence rate is defined

TABLE 3.2: **Variance Inflation Factor.** This table presents the Variance Inflation Factor (VIF) for independent variables of the panel-HAR regression. The VIF is computed as $VIF_i = \frac{1}{(1-R_i^2)}$ where R_i^2 is the unadjusted coefficient of determination for regressing the i th independent variable on the remaining ones. The daily sentiment and attention variables are computed from 1-minute observations between 16:00t and 09:25t+1.

	Baseline	ESG	News	Social	E	S	G
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>const</i>	1.03	1.03	1.03	1.03	1.03	1.03	1.04
<i>log Buzz</i>		1.08	1.02	1.03	1.1	1.05	1.15
<i>Sent</i>		1.0	1.03	1.01	1.16	1.01	1.03
<i>RVSent</i>		1.05	1.04	1.02	1.15	1.02	1.14
<i>RV^d</i>	2.15	2.18	2.16	2.18	2.16	2.18	2.17
<i>RV^w</i>	3.06	3.06	3.06	3.06	3.06	3.06	3.06
<i>RV^m</i>	1.85	1.85	1.85	1.85	1.85	1.85	1.85
<i>VIX</i>	1.41	1.41	1.41	1.41	1.41	1.41	1.41
<i>ΔVIX</i>	1.09	1.09	1.09	1.09	1.09	1.09	1.09

as the number of days where extreme sentiment is detected in each set occurring on the same day relative to the total number of days where extreme sentiment is detected. Put simply:

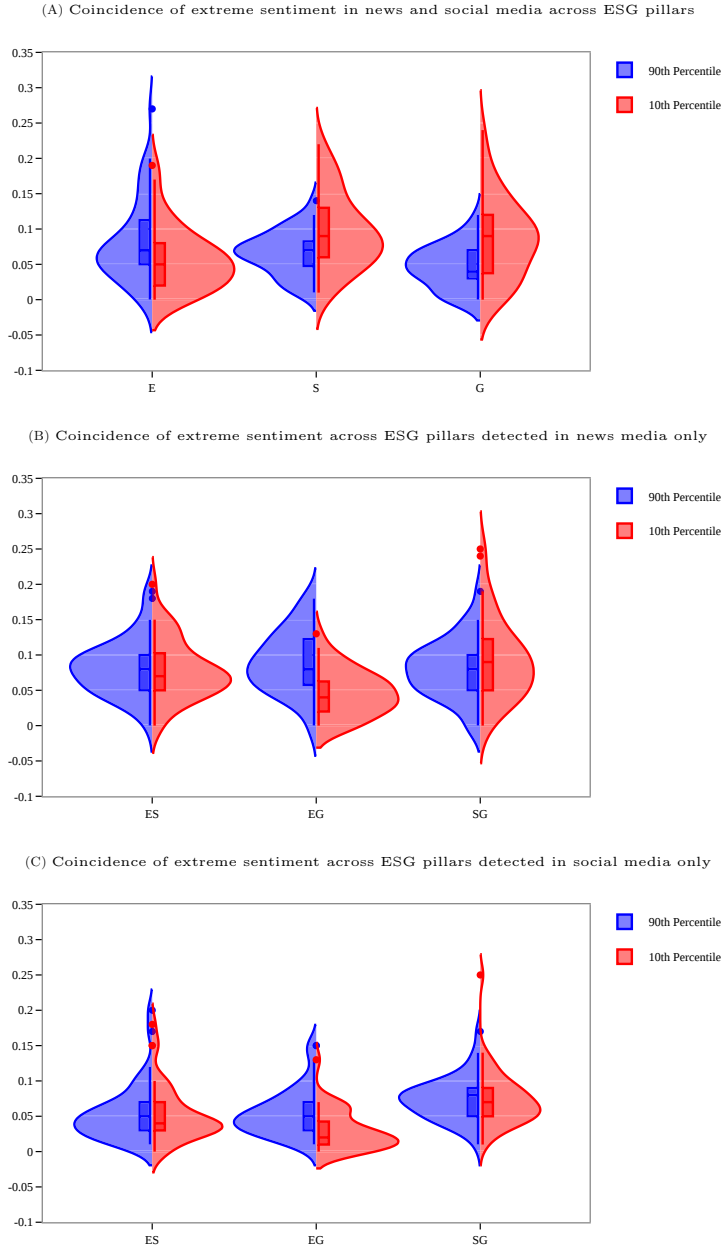
$$coincidenceRate_{P(x)>90,i} = \frac{|A_{P(x)>90} \cap B_{P(x)>90}|}{|A_{P(x)>90} \cup B_{P(x)>90}|} \quad (3.8)$$

where $A_{P(x)>90}$ represents the set of extreme events in variable A (e.g. Environmental sentiment derived from news media) and $B_{P(x)>90}$ represents the set of extreme events in variable B (e.g. Environmental sentiment derived from social media) for company j .

The premise of this exercise being that if the information presented in set A and set B have a high rate of coincidence, this implies that days of extreme sentiment are likely to occur at the same time and the difference in information provided is likely to be low. Hence the benefit of exploring the effect of ESG sentiment on stock price volatility, whether derived from news or social media is likely to be marginal.

Figure 3.2 presents the kernel density estimate of the proportion of days that overlap. We observe that the rates of coincidence are low not only between news and social media for each E, S and G pillar (Panel (3.2A)), but also between each of the pillars for news (Panel (3.2B)) and social media (Panel (3.2C)). This confirms that the information in social media and news media is of a different nature, and that the information differs across the pillars in both news and social media.

FIGURE 3.2: **Coincidence of extreme sentiment in news and social media.** This figure presents the kernel density estimate of the proportion of days for each firm where extreme sentiment was observed on the same day in news and social media (Panel (A)), or between pillars for news (Panel (B)), and social media (Panel (C)). Extreme sentiment is defined as the top (bottom) decile of the interacted term $\log Buzz_t \times Sent_t$ for each firm in the sample. The left hand side of the plots represent overlapping days of positive sentiment, whilst the right hand side represent negative sentiment. Panel (A) presents the coincidence of extreme sentiment that occur in news and social media for each E, S and G pillar. Panel (B) presents the coincidence of extreme sentiment that occur for the E and S pillars, E and G pillars, and S and G pillars for news. Panel (C) presents the same as Panel (B), but for social media. Sample period is from 1-Jan-2016 to 31-Dec-2021.



3.4 Methodology

To answer the question of whether ESG is relevant in explaining stock price volatility, we rely upon the heterogeneous autoregressive (HAR) model of Corsi (2009), extended to include macroeconomic co-variates and sentiment indicators in a manner similar to Audrino et al. (2020). The HAR model is a popular tool for forecasting volatility owing to its simplicity and accurate fit of financial volatility (Corsi et al., 2012; Audrino et al., 2020). Since its inception, the HAR model has undergone several extensions and analysis to improve forecasting power, such as the inclusion of jump variables (Andersen et al., 2007; Corsi et al., 2010), leverage effects (Corsi et al., 2012; Patton and Sheppard, 2015), non-parametric methods (Fengler et al., 2015), and adaptive methods (Audrino et al., 2015; Audrino and Knaus, 2016; Yao et al., 2019; Audrino et al., 2020).

When establishing the baseline model for our analysis, the choice of variables are an important consideration. For example, there is some debate as to whether the inclusion of jump variables make a difference when forecasting volatility. Andersen et al. (2007), Forsberg and Ghysels (2007), and Busch et al. (2011), find that jumps have limited value in this regard, whilst Patton and Sheppard (2015) finds that the impact of jumps depends on its sign. In recent analysis, Caporin (2023) shows that in many cases, the forecasting outcome are comparable to the classic-HAR model of Corsi (2009). For this reason, we ignore the inclusion of jump variables in our model.

Meanwhile, a second strand of literature shows that the inclusion of economic and financial variables can improve volatility forecasts (Christiansen et al., 2012; Paye, 2012; Mitnik et al., 2015) and are largely grouped into the following categories: *Equity market variables*, *Bond market variables*, *Exchange rate variables*, *Liquidity variables*, and *Macroeconomic variables* (see Christiansen et al., 2012; Audrino et al., 2020). Despite the vast array of variables that can be included however, Audrino et al. (2020) finds that out of 56 economic co-variates they had included in their analysis, only the VIX index was selected for all companies. Therefore, for parsimony we only include VIX and change in VIX as control variables for our model.

The baseline model we use in our analysis is given by:

$$\ln RV_{t+1}^d = \alpha + \beta^T(\ln \mathbf{RV}_t) + \lambda^T \mathbf{C}_t + \epsilon_{t+1} \quad (3.9)$$

where $\ln \mathbf{RV}_t$ is a 3-dimensional column-vector that contains the daily log realised volatilities,

and the weekly and monthly average daily log realised volatilities,⁷ and \mathbf{C}_t is the q -dimensional column vector of the economic control variables and firm fixed effects for the panel regressions.

Following on from the work by Audrino et al. (2020) volatility models are being extended to include measures that capture investor mood and attention to financially material topics. Much of this work however is centred on whether sentiment more broadly contributes to future realised volatility, and we are not aware of any works currently that decompose sentiment into different types, let alone sentiment with regard to ESG concerns. Therefore, a key feature of our model is the inclusion of the following ESG sentiment and attention measures: $RVSent_t$, $Sent_t$, and $\ln Buzz_t$. This gives the following model:

$$\ln RV_{t+1}^d = \alpha + \beta^T(\ln \mathbf{RV}_t) + \gamma^T \mathbf{ESG}_t + \lambda^T \mathbf{C}_t + \epsilon_{t+1} \quad (3.10)$$

where \mathbf{ESG}_t is a generalised 3-dimensional column vector that contains the ESG sentiment variables. We will refer to this model as HAR-ESG.

A key benefit of our sentiment data is its ability to decompose sentiment into its media type and pillar groups which we exploit to test hypotheses (H2a, b) and (H3a, b). Table 3.3 describes the models used in our analysis. In all instances, all variables included in the models are conditionally standardised over a 3-month rolling window to achieve a zero-mean and unit standard deviation.

TABLE 3.3: Model description

No.	Name	Description
1	Baseline-HAR	Eqn. 3.9
2	HAR- ESG_{NS}	Eqn. 3.10 for composite ESG score from news and social media
3	HAR- ESG_N	Eqn. 3.10 for composite ESG from news only
4	HAR- ESG_S	Eqn. 3.10 for composite ESG from social media only
5	HAR- E_{NS}	Eqn. 3.10 for the environmental pillar from news and social media
6	HAR- S_{NS}	Eqn. 3.10 for the social pillar from news and social media
7	HAR- G_{NS}	Eqn. 3.10 for the governance pillar from news and social media

We break our in-sample analysis into two segments. First we examine the average effect that the ESG sentiment variables, and in particular $RVSent$, has on explaining realised volatility by estimating a pooled balanced panel HAR of our baseline (Model 1) and HAR-ESG (Models 2-7) models with industry fixed effects. We control for industry rather than firm fixed effects as responses are expected to be similar across industry groups. This provides a direct method to

⁷The weekly and monthly daily log realised volatilities have been computed in the manner of Audrino et al. (2020), that is $\ln RV_t^w = \frac{1}{5} \sum_{i=1}^5 \ln RV_{t-i+1}^d$ and $\ln RV_t^m = \frac{1}{22} \sum_{i=1}^{22} \ln RV_{t-i+1}^d$

assess the significance of the ESG sentiment variables in a grouped setting (Patton and Sheppard, 2015). Second, we examine the effect that the ESG sentiment variables have on stock volatility at the individual company level.

3.5 Empirical Results

3.5.1 Panel Regressions

The results of the panel regressions are summarised in Table 3.4. Column (1) outlines the Baseline model. Column (2) details the composite ESG model, ESG_{NS} , where ESG sentiment is derived from all media. Columns (3) and (4) present the decomposed media models, ESG_N and ESG_S , where ESG sentiment is disaggregated into their media components. Columns (5) to (7) display the decomposed pillar models, E_{NS} , S_{NS} , and G_{NS} , where ESG sentiment are disaggregated into pillar groups.

TABLE 3.4: **Panel HAR Regression.** This table reports the estimated regression coefficients and t-statistics (in brackets) from the panel regressions for daily stock return volatility. The sample consists of 45 stocks (5 from each of the Refinitiv TRBC Economic Sectors excluding Real Estate Sector) and covers the period between 01-Jan-2016 and 31-Dec-2021. Column (1) presents the results of the baseline model. Column (2) present the results for Sentiment-HAR model for composite ESG and combined News and Social Media. Columns (3) and (4) present the results for the Sentiment-HAR models for the composite ESG sentiment derived from News and Social media respectively. Columns (5) to (7) present the results for the Sentiment-HAR model for E, S and G sentiment derived from News and Social media combined. RV^{Sent} , $Sent$, $\log Buzz$, are the realised volatility of sentiment, sentiment and $Buzz$ respectively. Daily measures of the sentiment and attention variables are computed from 1-minute observations between 16:00t and 09:25t+1. RV^d , RV^w , RV^m are the short, medium and long term measures of realised stock return volatility. VIX is the logarithm of the VIX index and ΔVIX is the percentage change in VIX . All models are controlled for Industry Fixed effects and use robust standard errors. ***, **, * indicates significance at the 1%, 5% and 10% levels respectively.

	Baseline (1)	ESG (2)	News (3)	Social (4)	E (5)	S (6)	G (7)
<i>const</i>	-0.0099 *** (-3.33)	-0.0108 *** (-3.66)	-0.0099 *** (-3.34)	-0.0098 *** (-3.31)	-0.0088 *** (-2.97)	-0.01 *** (-3.37)	-0.0071 ** (-2.39)
$\log Buzz$		0.0812 *** (24.22)	0.0529 *** (16.26)	0.0754 *** (22.92)	0.0396 *** (11.87)	0.0765 *** (23.09)	0.0591 *** (17.03)
<i>Sent</i>		-0.0015 (-0.49)	0.0044 (1.39)	-0.0075 ** (-2.45)	-0.0248 *** (-6.76)	0.0117 *** (3.83)	-0.0064 * (-1.85)
RV^{Sent}		0.0173 *** (5.24)	0.0097 *** (2.99)	0.008 ** (2.43)	0.0122 *** (3.7)	0.0072 ** (2.25)	0.007 ** (2.15)
RV^d	0.3559 *** (75.42)	0.3429 *** (72.59)	0.3501 *** (74.12)	0.3446 *** (72.97)	0.3522 *** (74.62)	0.3437 *** (72.79)	0.3482 *** (73.77)
RV^w	0.1602 *** (31.65)	0.1576 *** (31.21)	0.1591 *** (31.44)	0.1577 *** (31.23)	0.1597 *** (31.56)	0.158 *** (31.3)	0.1586 *** (31.36)
RV^m	0.0467 *** (14.22)	0.0489 *** (14.93)	0.0481 *** (14.67)	0.0484 *** (14.78)	0.0469 *** (14.3)	0.0485 *** (14.84)	0.0484 *** (14.77)
VIX	0.1227 *** (36.66)	0.1272 *** (38.14)	0.1247 *** (37.3)	0.1271 *** (38.09)	0.1242 *** (37.13)	0.1267 *** (38.0)	0.1255 *** (37.59)
ΔVIX	0.0479 *** (13.18)	0.0441 *** (12.14)	0.0461 *** (12.67)	0.0452 *** (12.46)	0.0469 *** (12.9)	0.0447 *** (12.31)	0.0467 *** (12.86)
R2	0.38	0.38	0.38	0.38	0.38	0.38	0.38
F-stat	9313.9	6005.46	5912.98	5989.87	5873.26	5994.08	5954.91
F-pvalue	0.0	0.0	0.0	0.0	0.0	0.0	0.0
nobs	70380	70380	70380	70380	70380	70380	70380
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Key findings broadly support our first hypothesis, that an increase in the realised volatility of sentiment (H1a, H2a, H3a) and an increase in media attention (H1b) are associated with an increase in stock price volatility. The results show that a one-standard deviation increase $RVSent$ leads to an economic and significant increase in stock price volatility of between 0.7% and 1.73%. In *Buzz* meanwhile, reveals an economically larger, and significant, impact on stock price volatility that ranges between 3.96% and 8.12%. These findings are consistent with Audrino et al. (2020), and support the findings of Kölbel et al. (2017) who link higher media coverage with increased risk.

The impact of $RVSent$ on volatility was slightly lower in social media than for news media, although economically, they were similar at 0.8% and 0.97% respectively. This contrasts with the expectations outlined in Hypothesis H2b that social media would have a greater impact. Although at first glance these findings appear to contradict Gan et al. (2020), their study focuses on general news coverage. This study meanwhile specifically examines ESG discussions which may capture a more specialised investor audience, potentially explaining the observed differences in media impact. In practical terms, these findings suggest that discussion of ESG topics in news media has a greater financial impact than discussion in social media. This study therefore allows for the isolation of investor responses tied to discussion of ESG topics and indicates a preference for the medium used for news consumption. For investors and companies, this suggests prioritising engagement with news media outlets when communicating ESG initiative to maximise financial impact. When reviewing the decomposed pillar models, we find that the environmental pillar had a larger impact at 1.22% which was in line with our expectations regarding Hypothesis H3b.

The *Sent* variable produced mixed and counter-intuitive interpretations. We expect to see a decrease in volatility as sentiment becomes more positive due to the asymmetric response of positive vs negative news (Ho et al., 2013). From an ESG perspective, positive sentiment implies that the company is taking positive action either in improving ESG performance, or investing in CSR activities, which are associated with an improved risk profile (Nirino et al., 2022). Whilst this view is consistent for social media (ESG_S), the environmental pillar (E_{NS}), and the governance pillar (G_{NS}), we find the opposite effect for the social pillar (S_{NS}).⁸ One possible explanation is that investors may view activity on social issues as being costly for which the future benefit is uncertain (Malshe et al., 2023). Social issues are notoriously subjective, and

⁸The sign of the coefficient for news media, ESG_N is also positive and counterintuitive, however we ignore it as it was neither economically or statistically significant.

what may be seen as “good” in the public’s eye, may be perceived by investors as an erosion of shareholder value.

3.5.2 Individual HAR

In this section we estimate the ESG-HAR models separately for each company to assess the individual impact of ESG sentiment on stock price volatility. We first ascertain whether the addition of sentiment variables jointly provide explanatory power in addition to the baseline model. Using the model specified in Eqn. 3.10, we consider the hypothesis:

$$\begin{aligned} H_0 : \gamma_i &= 0, & \forall i = 1, \dots, k \\ H_a : \gamma_i &\neq 0, & \text{for at least one } i \end{aligned} \quad (3.11)$$

where k is the number of ESG sentiment variables. We test the null hypothesis given in Eqn. 3.11 for each company using an F-test to compare the HAR-ESG models against the baseline. A summary of the joint tests alongside goodness-of-fit measures are presented in Table 3.5.⁹ The first row presents the proportion of companies from the sample that reported significant F-test. The remaining rows display the average change of ESG-model fit against the baseline using three goodness-of-fit measures: Adjusted R^2 (henceforth R^2), Akaike information criterion (AIC), and Bayes information criterion (BIC). A positive (negative) number in the change of R^2 (AIC and BIC) implies that model fit was improved by the inclusion of sentiment and attention variables.

TABLE 3.5: **Summary of individual in-sample regressions.** This table summarises the regression results of the 45 stock-level regressions for daily stock return volatility. The first row in each panel reports the proportion of stocks with significant F-statistics. The remaining rows report the average improvements in three goodness-of-fit measures considered for the in-sample analysis: R^2 , the Akaike information criterion (AIC), and the Bayes information criterion (BIC). Joint significance are obtained for each stock by comparing the sentiment-HAR models (unrestricted) against the baseline model (restricted). The daily sentiment and attention variables were aggregated from 1-minute observations between 16:00 t and 09:25 $t+1$. The sample period is from 01-Jan-2016 to 31-Dec-2021.

	ESG (2)	News (3)	Social (4)	E (5)	S (6)	G (7)
Proportion of companies with significant F-test	82.22	66.67	66.67	42.22	71.11	68.89
Average change of R^2 (in %)	0.86	0.18	1.10	0.12	0.81	0.41
Average change of AIC (in %)	-0.07	0.05	-0.13	0.03	-0.05	-0.02
Average change of BIC (in %)	0.37	0.48	0.31	0.47	0.39	0.41

These results indicate that for the majority of companies sampled, the addition of ESG sentiment and attention variables improve the explanatory power of the baseline model. ESG_{NS} had the largest proportion of companies with statistically significant F-test at 82.22% or 37 of 45

⁹Refer to Table A.2.4 in Appendix A.2 to view the joint significance of the ESG models against the baseline for individual companies.

companies. The environmental pillar E_{NS} had the lowest proportion, revealing only 42.22% of companies reported a significant F-test, suggesting that sentiment relating to the environment may be less informative to predicting stock price volatility. Additionally, it was not clear whether the inclusion of sentiment and attention variables improved model fit, as the goodness-of-fit tests were conflicting. For example, the R^2 measure implies that the addition of sentiment and attention variables improved model fit by between 0.12 and 1.10%, whereas the BIC measure implies it worsened by between 0.31 and 0.48%.

Finally, we contrast models based on their decomposition groups to test hypotheses H2a,b for media type, and H3a,b for the pillars. We do this in two ways. Statistically, by computing the average difference in F-statistics between the pair of models being compared, (i.e Type A sentiment - Type B sentiment), and visually by plotting the coefficients of $RVSent$, with Type A sentiment along the x-axis and Type B sentiment along the y-axis. For the media type group, the F-statistics for model ESG_S was subtracted from ESG_N (i.e news minus social media). For the pillar groups, the F-statistics for model S_{NS} was subtracted from E_{NS} (environmental minus social pillar), model G_{NS} was subtracted from E_{NS} (environmental minus governance pillar), and model G_{NS} was subtracted from S_{NS} (social minus governance pillar). A positive difference in F-statistics implies that the model with Type A sentiment has better explainable power than the model with Type B sentiment. The average difference in F-statistics for each pair are presented in Table 3.6.

TABLE 3.6: **Contrasting ESG decomposition.** This table presents the matched difference in F-statistics between the decomposed ESG groups, i.e. media type and pillar. In computing the matched difference, we take the F-statistic of the in-sample regressions from Type B sentiment (e.g. Social) and subtract from Type A sentiment (e.g. News) for each company in our sample, then the average is taken. A negative value implies that on average, the F-statistics from Type B sentiment was larger and that the model based on Type B sentiment was better at explaining realised volatility. Our sample consists of 45 companies. The sample period is between 01 Jan 2016 and 31 Dec 2021.

	Average diff in F-stat
News vs Social	-3.36
Environment vs Social	-3.24
Environment vs Governance	-1.30
Social vs Governance	1.94

In line with our expectations regarding H2a,b, the results suggest that social media has greater explainable power compared with news media in individual tests. This is confirmed when contrasting the sensitivity of the $RVSent$ coefficients between ESG_N and ESG_S models (see Figure 3.3). Meanwhile, contrary to expectations outlined in H3b and the findings from the panel regressions in Section 3.5.1, the results here show the social pillar having the greatest impact to realised volatility and the environmental pillar the weakest in individual regressions.

The difference in findings between the two regression methodologies suggest that social factors play a more prominent role in influencing market volatility for a larger number of companies in this sample, a nuance that is lost in aggregate. These contrasting results reinforce support for the literature that advocates for E, S, and G pillars to be examined individually owing to the idiosyncratic responses to risk. The result for the social pillar is further confirmed when we contrast the differences in the coefficient of $RVSent$ against the environmental and governance pillar groups in panels (A) and (C) of Figure 3.4, however are slightly weighted towards the environmental pillar as shown in panel (B).

FIGURE 3.3: **Sensitivity to sentiment - News vs Social.** This figure compares the economic impact of $RVSent$ derived from news and social media on stock price volatility. This figure plots the coefficient for $RVSent$ from $HAR-ESG_N$ (x-axis) and $HAR-ESG_S$ (y-axis) from in-sample regressions for the 45 firms in our sample. The size of the markers represent the maximum t-stat between $RVSent$ of the models being compared. The colours of the markers represent the sector groups that the firms belong to. Sample period is between 01-Jan-2016 and 31-Dec-2021.

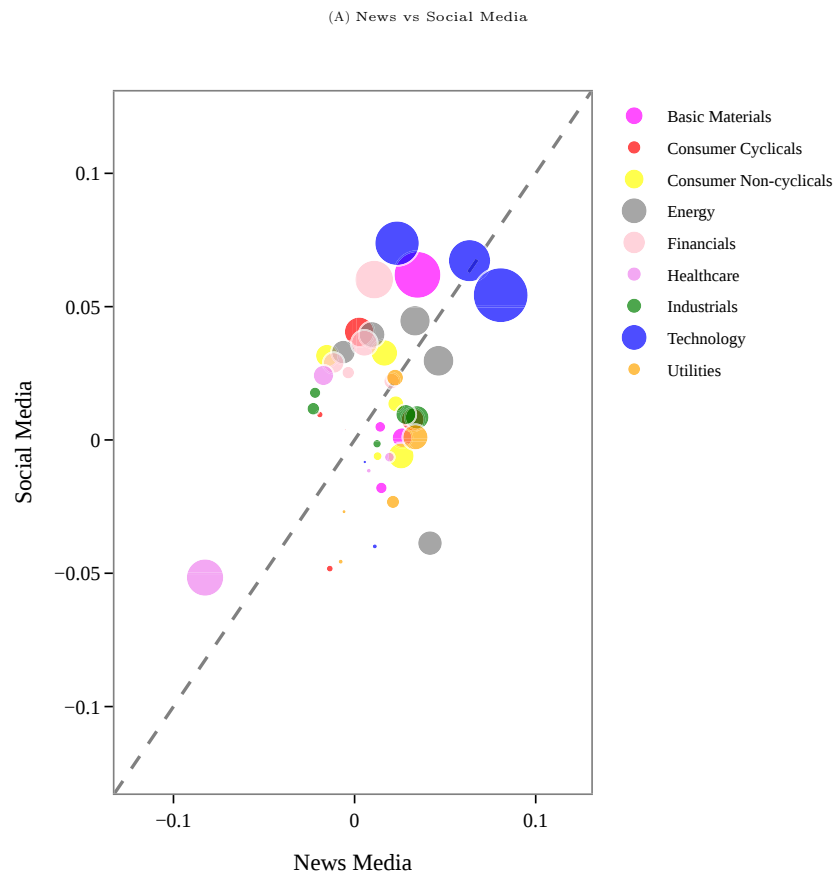
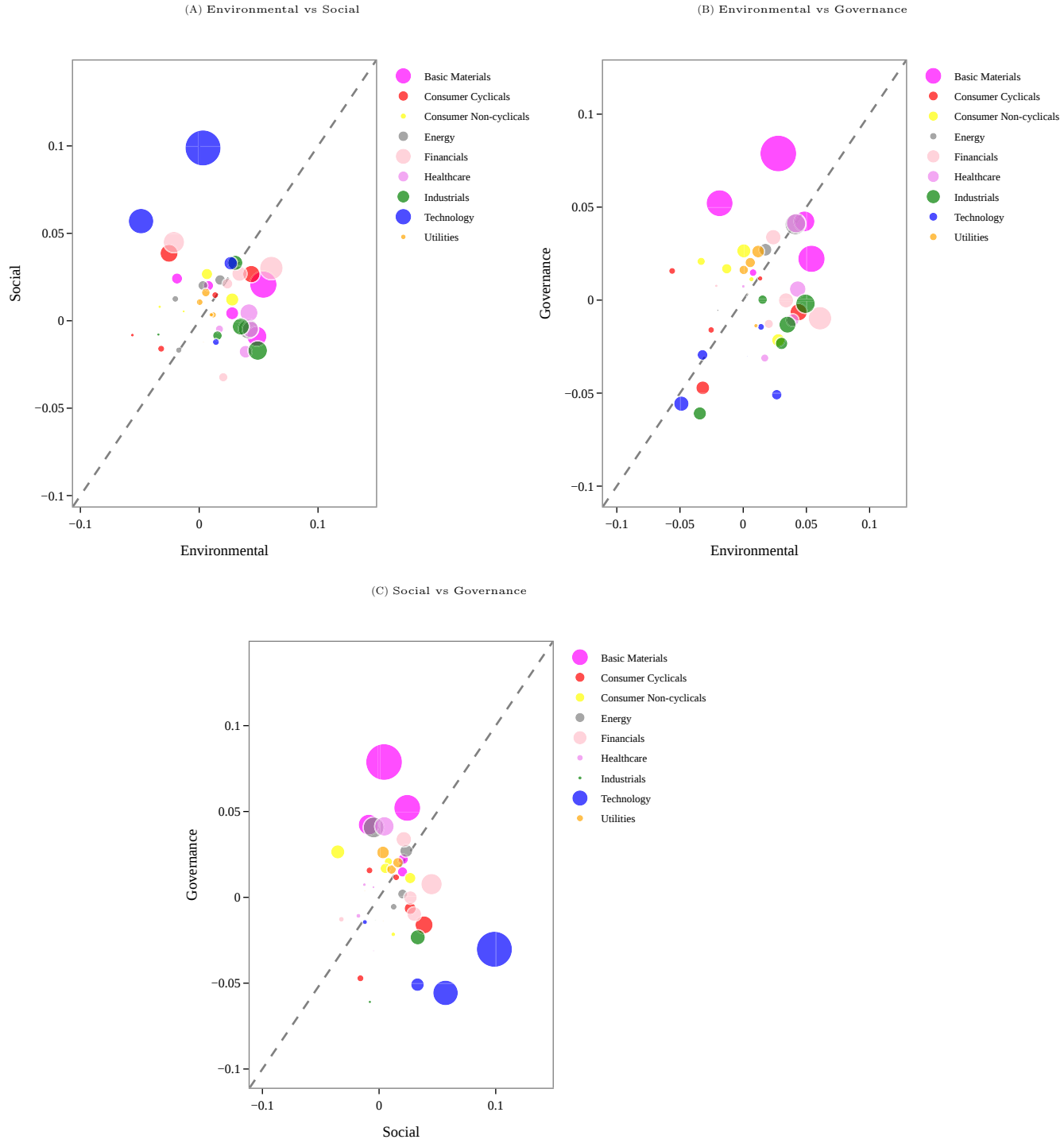


FIGURE 3.4: **Sensitivity to sentiment - E vs S vs G.** This figure compares the economic impact of RV_{Sent} derived from news and social media on firm volatility. Panel (A) plots the coefficient for RV_{Sent} for the HAR-ESG model with the RV_{Sent} coefficients from HAR- E_{NS} on the x-axis and HAR- S_{NS} on the y-axis from in-sample regressions for the 45 firms in our sample. Panels (B) and (C) present the same, but for HAR- E_{NS} (x-axis) and HAR- G_{NS} (y-axis), and HAR- S_{NS} (x-axis) and HAR- G_{NS} (y-axis) respectively. The size of the markers represent the maximum t-stat between RV_{Sent} of the models being compared. The colours of the markers represent the sector groups that the firms belong to. Sample period is between 01-Jan-2016 and 31-Dec-2021.



3.5.3 Sensitivity to overnight sentiment

In this section we present alternative windows over which to aggregate the sentiment and attention variables from 1-minute observations to a daily frequency. The purpose of this extended analysis is to ensure that our findings are robust to a daily sentiment measure determined over different definitions of a “day”. In our main results, the sentiment measure captures only overnight sentiment based on the findings of Gan et al. (2024) who find that overnight sentiment improves predictability in forecasting return models. Variations to the aggregation window include considering the trading day and overnight sentiment, trading day only, and a day in the traditional sense. The window lengths for each variation are listed in Table 3.7:

TABLE 3.7: **Sentiment aggregation windows.** This table presents varying windows over which to aggregate 1-minute observations to daily in the sentiment and attention variables.

Definition	Aggregation window
Trading day + overnight sentiment	9:35 t to 09:25 $t+1$
Trading day only	09:35 t to 15:55 t
Calendar day	00:00 t to 23:59 t

A summary of results of the panel-HAR regressions are presented in Table 3.8. Panel A presents the main results for ease of comparison, Panel B presents the results when observations are aggregated to include sentiment throughout the trading day and overnight, Panel C presents results for sentiment during the trading day only, and Panel D presents the results for sentiment during the traditional definition of a day. For brevity, only the variables of interest, $\ln Buzz$, $Sent$, and $RVSent$, are displayed. Our results are strongest when only overnight sentiment are used to forecast volatility and weakest when sentiment is aggregated over a calendar day. $\ln Buzz$ demonstrates the most consistency over the different day definitions, indicating that media attention is a strong contributor to stock price volatility. Similar conclusions regarding the optimal time frame for the sentiment aggregation window are reached when contrasting the results of individual HAR. Table 3.9 presents the proportion of companies with significant F-test over the varying windows.

3.6 Forecasting volatility with ESG sentiment

This section presents the forecasting methodology and results for the models considered, baseline-HAR and HAR-ESG. The models are estimated using a rolling window of 252 days, which corresponds to approximately 1 year. Once the models have been estimated, 1-step ahead forecasts

TABLE 3.8: **Varying sentiment aggregation windows.** This table presents the Panel-HAR regression results for daily stock return volatility using different windows to aggregate the independent sentiment variables to a daily frequency. Panel A reports the results for a trading day + overnight sentiment (09:35t to 09:25t-1), Panel B covers trading day only (09:35t to 15:59t), and Panel C presents for a traditional 24hr day (00:00t to 23:59t). The sample consists of 45 stocks and covers the period between 01-Jan-2016 and 31-Dec-2021. Column (1) present for Sentiment-HAR model for composite ESG and combined News and Social Media. Columns (2) and (3) present for the Sentiment-HAR models for the composite ESG sentiment derived from News and Social media respectively. Columns (4) to (6) present for the Sentiment-HAR model for E, S and G sentiment derived from News and Social media combined. RV_{Sent} , $Sent$, $\log Buzz$, are the realised volatility of sentiment, sentiment and $Buzz$ respectively. For brevity only the sentiment and attention variables are displayed. All models are controlled for Industry Fixed effects and use robust standard errors. ***, **, * indicates significance at the 1%, 5% and 10% levels respectively.

Panel A: Trading day + overnight sentiment						
	ESG_{NS}	ESG_N	ESG_S	E_{NS}	S_{NS}	G_{NS}
	(1)	(2)	(3)	(4)	(5)	(6)
$\log Buzz$	0.0721 *** (21.1)	0.044 *** (13.39)	0.0712 *** (21.49)	0.0347 *** (10.23)	0.0688 *** (20.54)	0.0635 *** (17.64)
$Sent$	-0.0007 (-0.23)	0.0021 (0.67)	-0.0025 (-0.81)	-0.0233 *** (-6.35)	0.0114 *** (3.69)	-0.0099 *** (-2.91)
RV_{Sent}	0.0124 *** (3.65)	0.0081 ** (2.44)	0.0018 (0.54)	0.0063 * (1.85)	0.0028 (0.86)	-0.0035 (-1.01)
Panel B: Trading day only						
$\log Buzz$	0.0213 *** (6.48)	0.0037 (1.16)	0.029 *** (9.03)	0.0074 ** (2.28)	0.0221 *** (6.8)	0.0183 *** (5.43)
$Sent$	-0.0044 (-1.43)	-0.0007 (-0.21)	0.002 (0.63)	-0.0104 *** (-2.79)	-0.002 (-0.64)	-0.0064 * (-1.86)
RV_{Sent}	0.0009 (0.27)	0.0062 * (1.9)	-0.0074 ** (-2.22)	0.0008 (0.24)	0.0019 (0.59)	0.0018 (0.57)
Panel C: Calendar Day						
$\log Buzz$	0.04 *** (11.72)	0.0194 *** (5.96)	0.0476 *** (14.51)	0.0178 *** (5.26)	0.0394 *** (11.86)	0.0327 *** (9.08)
$Sent$	-0.0009 (-0.29)	0.0013 (0.4)	-0.0016 (-0.52)	-0.0148 *** (-4.04)	0.0063 ** (2.04)	-0.0044 (-1.29)
RV_{Sent}	0.0038 (1.11)	-0.0003 (-0.1)	-0.0049 (-1.45)	0.0068 ** (2.0)	0.0011 (0.35)	0.0029 (0.85)

TABLE 3.9: **Proportion of companies with significant F-test.** This table presents the proportion of companies with significant F-test of the 45 stock-level regressions using different windows to aggregate the independent sentiment variables to a daily frequency. Joint significance are obtained for each stock by comparing the sentiment-HAR models (unrestricted) against the baseline model (restricted). The sample period is from 01-Jan-2016 to 31-Dec-2021.

	ESG_{NS}	ESG_N	ESG_S	E_{NS}	S_{NS}	G_{NS}
	(1)	(2)	(3)	(4)	(5)	(6)
Trading day + overnight sentiment	77.78	48.89	62.22	42.22	73.33	71.11
Trading day only	20.00	6.67	17.78	11.11	20.00	17.78
Calendar day	35.56	17.78	44.44	20.00	35.56	33.33

are produced. Due to the different scales of the input variables, all variables within the estimation period are normalised to zero mean and unit standard-deviation. To ensure the sentiment and media attention variables are sufficiently persistent to justify their use as such instruments, the variables were tested for persistence using an AR(1) model. Table A.2.3 in Appendix A.2

presents the proportion of stocks with significant first lag coefficients. The variables within the prediction period are normalised using the mean and standard deviation derived from the estimation period. The normalised values in both the estimation and prediction periods are winzorised at 95% confidence interval to remove outliers. The estimation window is then rolled over by one day and the procedure is repeated. The out of sample accuracies of the models are assessed using the mean square prediction error (MSPE) defined as:

$$MSPE_{(J)} = \frac{1}{T} \sum_{t=1}^T e_{(J)}^2 \quad (3.12)$$

where T is the total number of predictions made, and J denotes the model that is used, i.e. $J \in \{\text{baseline-HAR, HAR-ESG}_{NS}, \text{HAR-ESG}_N, \text{HAR-ESG}_S, \text{HAR-E}_{NS}, \text{HAR-S}_{NS}, \text{HAR-G}_{NS}\}$. The forecasting error of model J is denoted by $e_{(J)}$ and defined as:

$$e_{(J)} = \log RV_{t+1}^Z - \hat{y}^Z \quad (3.13)$$

where Z indicates that normalised variables have been used. Since we are comparing nested models, we adjust MSPE of the nested models by the Clark and West (2007) adjustment factor. The adjusted MSPE is given by:

$$MSPE_{adj} = MSPE_K - \frac{1}{T} \sum (\hat{y}_{B,t+h} - \hat{y}_{K,t+h})^2 \quad (3.14)$$

where T is the total number of predictions used in computing the average, $\hat{y}_{B,t+h}$ are the predictions obtained from the baseline model, and $\hat{y}_{K,t+h}$ are the predictions obtained from the nested model. The testing procedure (CW test) to ascertain the MSPE for the nested models is significantly different (lower) to the MSPE of the baseline model in one-tail tests.

In addition to reporting the mean squared prediction error, we also compute the out of sample R^2 using the method proposed by Campbell and Thompson (2008):

$$R_{oos}^2 = 1 - \frac{\sum (y - \hat{y})^2}{\sum (y - \bar{y})^2} \quad (3.15)$$

Table 3.10 reports the average reduction in MSPE from the baseline-HAR of the one-day ahead forecast results for the models analysed. The MSPE and out of sample R^2 for individual companies are presented in Tables A.2.5 and A.2.6 respectively, in Appendix A.2.

We observe significant forecasting improvement from the baseline-HAR in all of our models.

TABLE 3.10: **Average reduction in MSPE.** This table reports the average decrease in out-of-sample mean squared prediction error (MSPE) for HAR-ESG relative to the Baseline HAR of individual stocks. The one-day-ahead forecasts are estimated using a rolling 252 day window between 01-Jan-2016 and 31-Dec-2021. All variables within the estimation period are standardised to zero mean and unit standard deviation. Normalised values are windsorized at 95% to remove outliers. A negative value in the first row indicates that, on average, the MSPE for individual stocks was lower than that the baseline model. The second row presents the proportion of stocks with significant p-values of the Clark-West test of the HAR-ESG over the Baseline-HAR.

	ESG	News	Social	E	S	G
	(2)	(3)	(4)	(5)	(6)	(7)
average change in MSE (in %)	-2.22	-1.31	-2.33	-1.39	-1.99	-1.82
% of significant change	68.89	48.89	57.78	51.11	60.00	55.56

The greatest average reduction in MSPE was achieved from the HAR- ESG_S , followed closely by HAR- ESG_{NS} with average decreases in MSPE of -2.33 and -2.22 respectively. This suggests that the best outcome for volatility forecasting contrary to the literature that supports individual analysis of ESG components is to consider the combination of ESG performance. Consistent with our expectations of hypothesis (H2b), ESG sentiment variables derived from social media reported greater improvement in MSPE. However once again, contrary to our expectations in (H3b), the social pillar reported the greatest improvement in MSPE.

3.7 Discussion

This analysis finds that the predictability of stock-price volatility are greatly improved when ESG sentiment and attention variables are included in volatility models. These findings are consistent with the conclusions drawn by Audrino et al. (2020), who perform similar analysis on investor sentiment more generally. In answering the question “Does uncertainty in ESG increase risk?”, our research shows that the average effect of $RVSent$ on stock price volatility is both economically and statistically significant across all variants of the ESG-HAR models.

The novelty of this research is in the break-down of ESG sentiment based on media source, and by its pillar group, to dissect the impact of individual components of media and ESG on volatility. Our analysis differs from related literature in a two ways. First, our exclusive focus on ESG sentiment differs from prior research that investigate the impact of sentiment broadly on stock price variables (Sun et al., 2016; Gan et al., 2020). Second, by investigating the impact of ESG sentiment from both news and social media on volatility, it also differs from related literature that draws attention to stock price returns in response to ESG news (Flammer, 2013; Kölbel et al., 2017; Capelle-Blancard and Petit, 2019). The literature utilising social media is small, but burgeoning (Nicolas et al., 2024). Therefore, by incorporating ESG from social media

into our study we also contribute to this growing pool.

Our research reveals that not all measures of sentiment are equal in its effect on volatility, with sentiment and attention variables derived from social media having a greater impact at explaining and predicting volatility than for news media. Similarly, we find sentiment and attention on social topics had the strongest impact on volatility, whilst the environmental pillar had the weakest effect. Our findings also reveal that the attention variables have a non-trivial influence on stock price volatility that should not be ignored.

It was surprising to find that we obtained better out of sample forecasts when the information signals were combined into a single measure, that is composite ESG incorporating sentiment from both news and social media. This seems at odds with the literature that advocates for the separation of ESG performance measures into their respective pillar groups for analysis (see Berg et al., 2022; Malshe et al., 2023; Saini et al., 2025). One possible explanation for this result is that less data is available when the sentiment variables are decomposed into their respective groups leading to a weaker signal. The diluting of the sentiment and attention signals is more likely to affect smaller companies, or companies that receive less attention. This highlights a potential weakness in using sentiment data for this type of analysis. Future research may want to explore alternative higher-frequency measures of ESG.

While the isolation of ESG discussion from news topics more generally is the focal point of this research, a question remains as to whether the results would hold if sentiment measures of Audrino et al. (2020) had been included in the analysis. This is an interesting question and it is not immediately clear of what the outcome would be. In some respects, the ESG variables could be considered as subsets of sentiment and attention variables that capture company specific news and social media commentary more broadly. As such, there is a high possibility that the ESG variables may be considered informationally redundant. If this is the case, it is unlikely that the findings here will be significant, however future research may want to confirm this outcome. It is important to note, however, that the power of this analysis is in the decomposition of topics. Unlike aggregate sentiment measures, topic decomposition allows for the identification of specific ESG themes that may have distinct financial impacts, thereby offering more granular insights for investors and policymakers.

There may be a concern that as we establish the association between ESG and volatility, that our analysis may be subject to potential endogeneity and causality issues. In other words, that volatility drives sentiment, rather than the other way around. In our regression model, we lag the sentiment and control variables by one day relative to volatility. This ensures there is no

overlap, look-ahead bias, or contemporaneous relationship between the sentiment and volatility variables, and that the sentiment variables temporally precede volatility variables. This temporal precedence is crucial for establishing causality, as it rules out the possibility of the sentiment variables being influenced by the volatility variables within the same time frame. Through this careful modelling of variables and their association with time, we confidently attribute changes in volatility to prior sentiment, reinforcing the robustness of our causal inferences.

These findings have important implications for volatility modelling, particularly as ESG concerns are increasingly being incorporated into investor portfolios. The strong results indicate that not only should ESG factors be added to volatility models, but that omitting them could lead to underestimation of risk when forecasting volatility. This is particularly pertinent for risk managers in estimating Value-at-Risk, and for portfolio managers in managing exposures.

Although our work provides some insights into the characteristics of ESG sentiment and impact on stock price volatility, it does not optimise on the combination of ESG sentiment for forecasting volatility. Moreover it does not provide a temporal analysis and whether the ESG sentiment variables persist through time. Therefore future work could involve performing this analysis under a clustering or lasso framework similar to Audrino and Knaus (2016), Audrino et al. (2020) or Yao et al. (2019). Moreover, ESG sentiment is only one element of the set of ESG measures. Further research may investigate combining ESG sentiment with other qualitative and quantitative measures of ESG to examine whether this measure yields better improvement.

3.8 Conclusion

This chapter investigates the impact of ESG sentiment on stock price volatility. The inclusion of ESG sentiment and attention variables significantly enhances the explanation and prediction of stock price volatility. When contrasting ESG sentiment decomposed into media source, we find social media to be a better predictor of stock price volatility. Results vary however when we contrast ESG sentiment decomposed into the pillar groups. Despite literature advocating for separate analysis on environmental, social, and governance topics, we discover that the ESG composite score yields better out-of-sample forecasts. Importantly, we find that overnight sentiment plays a crucial role in explaining volatility.

These results highlight the importance of including ESG measures in volatility models, but reveal that more is required to understand the dynamics between ESG and risk. This research has practical implications for risk managers and investors where sustainability is integrated

with investment-decision making. For example, risk managers could incorporate ESG sentiment measures into forecasting models to account for the contribution of risk from ESG. Meanwhile, investors might monitor overnight sentiment and media attention to anticipate market movements associated with sustainability concerns. Future research could extend this analysis over different market-regimes and markets.

Chapter 4

Breaking Buzz! Extracting materiality from media attention

4.1 Introduction

The question of whether green stocks outperform brown stocks has been a source of contention for more than a decade, the answer to which continues to elude researchers. The question is so frequently posed that even several meta studies¹ have been done to make sense of the enormous body of work that has gone into answering that one simple question. The equilibrium model of Pástor et al. (2021) posit that green assets should earn lower future expected returns. This is because green companies benefit from a lower cost of capital (Seltzer et al., 2022) and are perceived to be less risky (Chan et al., 2020; Hoepner et al., 2024). Empirical studies however, contradict this view, revealing a positive “greenium” when the returns of brown stocks are subtracted from their green counterparts (Brandon et al., 2020; Pástor et al., 2022).

Pástor et al. (2022) make an important distinction between expected and realised returns - that while the expected returns are predicted to be lower for green stocks, the realised returns are not. The discrepancy between expected and realised return is frequently attributed to an increased preference for sustainable assets, driving asset prices higher due to investor demand for green assets. While the specific reasons for this phenomenon vary, they can generally be summarised as being related to some form of “shock.” For instance, Pástor et al. (2022) finds

¹See Atz et al. (2023) and Whelan et al. (2021) for recent examples of meta studies that waded through the plethora of research that attempts to answer this question.

that once climate shocks are accounted for the outperformance of green stocks disappears whilst Ardia et al. (2023) relate increased stock prices of green firms to unexpected increases to climate change.

We offer an alternative explanation to the greenium debate. That the outsized realised returns of green assets may be attributed in part to a classification error. Decisions on whether assets are classified as green or brown are currently based on measures of ESG performance, such as ESG ratings (traditional ESG), that are backward looking and update only annually. As such, they are slow to update to new information, and as a result a stock may be classified as green for longer than they should be (vis-a-vis for brown stocks).

To understand how stocks may be misclassified, we perform the following thought experiment. Consider a company that is rated highly in terms of ESG (relative to the market), and the characteristics of the company are consistent with the rating it has. This company would be classified as a green stock, and has low future expected returns. Suppose as time goes by, an event (or series of events) occur that significantly alters the the characteristics of the company in the negative. The company's characteristics are now more in line with those of a brown stock. The events also have a negative impact on the company's stock price and the company's stock is now predicted to generate higher expected returns owing now to the perceived increased risk. However, because of the delay in updating the ESG rating to reflect current events, the company is still classified as green. As such, the returns of a portfolio of green stocks is now conflated with the higher expected returns of companies that would be considered brown if the measurement were current. Conversely, the returns of the brown portfolio will be weakened by the lower expected return of the companies that are truly green, but classified as brown. With this in mind, we hypothesise that the issue of the greenium whether it exists is a timing issue, and that using a more timely measure of ESG performance, the "equity greenium" reported by Pástor et al. (2022), would in fact be neutral or negative. We therefore aim to answer the following research question: Does increasing the timeliness of the ESG performance measure result in a negative equity greenium?

We answer this question empirically by employing a higher frequency measure of ESG performance derived from news and social media. We construct a value-weighted green minus brown (GMB) factor and compare it with a GMB factor formed using traditional ESG ratings (GMB-PST). Central to the formation of the GMB factor is the creation of the Breaking Buzz! metric - a novel approach to constructing media-based ESG scores.

Thus, one of the key contributions of this paper is the introduction of the Breaking Buzz!

metric, a novel approach to constructing media-based ESG scores that are independent of company influence and critically, available at much higher frequencies. This measure has a number of benefits. First, it is a dynamic measure and is able to quickly reflect changes in a company's characteristic profile. Second, the Breaking Buzz! metric accounts for materiality of discussion in context of its own history. This normalisation then allows the measure to be compared in the cross-section.

Our findings reveal that the GMB factor consistently reveals lower cumulative returns in the GMB factor compared with the cumulative returns of the GMB-PST factor. Moreover, we find equity greenium that is not significantly different from zero, indicating that the frequency of the ESG performance measure can materially affect the equity greenium. This is in contrast to the findings of Pástor et al. (2022) who obtain alphas that are both economically and statistically significant. These results are consistent across the environmental, social, and governance pillar groups, for equally-weighted portfolios, and different variations of the Breaking Buzz! measure.

We contribute to the literature in the following ways. First, we propose a novel method for measuring materiality from sentiment data which we call Breaking Buzz!. The measure is formed by computing the ratio of the current month's *Buzz* for a company with the average *Buzz* of the prior k months, excluding the current month. A Breaking Buzz! measure of 1 implies that media attention for the company is consistent with its recent history. A measure greater than 1 however implies that higher than normal activity is detected. The higher the number, the more salient the discussion of a companies activities within the pillar are, and therefore must be material in the public's view. To the best of our knowledge we are the first to propose and use such a measure in this way. Second, we extend the work of Pástor et al. (2022) to include analysis of the social and governance pillars. Whilst in recent times, much research has focused on environmental issues such as climate change, (Engle et al., 2020; Pástor et al., 2022), it would be remiss to ignore the other pillars. Third, we contribute to the expected vs realised quagmire by suggesting that the outperformance of green relative to brown portfolios may be linked to mis-classification of green and brown stocks. Finally, through our analysis, we add our voice to the chorus of academics and practitioners (Chatterji et al., 2016; Berg et al., 2022) highlighting the issues with existing measures of ESG performance, but has important implications for portfolio construction, and those investors or policy makers seeking to integrate sustainability into financial decision-making.

The rest of this chapter is organised as follows. The next section relates this research to the existing literature and provides a motivation for this study. Section 4.3 describes the data. Section 4.4 outlines the methodology used to construct the GMB factor. Section 4.5 presents

the results of the empirical analysis. In Section 4.6 we discuss the results and implications for further research. Finally, Section 4.7 concludes.

4.2 Related Literature

This research is related to the extensive literature that investigates the returns of green versus brown assets. Additionally it addresses the broader concept of the “equity greenium”, which empirically examines whether investors are willing to accept lower stock returns in exchange for non-pecuniary benefit. The equity greenium is defined by Pástor et al. (2022) as the difference between the expected returns of green and brown stocks, i.e. the expected return of a GMB portfolio. Despite the literature spanning more than decade there is still a lack of consensus on the relative performance of green assets.

One set of studies suggests that the returns for green assets should be lower than their brown counterparts. For example, through predictions in equilibrium models (Pástor et al., 2021), comparisons in implied cost of capital (El Ghouli et al., 2011; Chava, 2014), and via empirical observation (Hong and Kacperczyk, 2009; Baker et al., 2022; Berle et al., 2022; Seltzer et al., 2022; Zerbib, 2022; Bolton and Kacperczyk, 2023). Other studies however, find the opposite to be true (Eccles et al., 2014; Verheyden et al., 2016; Pástor et al., 2022). Pástor et al. (2022) make an important distinction between expected and realised return: that whilst returns for green stocks are expected to be lower than brown, the realised returns may not be. Moreover, once concerns for climate are taken into account, the outperformance of green stocks are neutralised, suggesting investor preferences for green stocks drive temporary positive price pressure. Several other studies also link outperformance of green stocks to investor preferences (Brandon et al., 2020; Van der Beck, 2021; Ardia et al., 2023; Cao et al., 2023).

We contribute to this literature by providing an alternative explanation for the discrepancy between expected and realised returns of green stocks. We show that using a higher frequency measure of ESG performance can result in the returns of a portfolio of green stocks that are either not significantly different from, or lower than a portfolio of brown stocks. Whilst we do not detract from the important work linking outperformance of green stocks to investor preferences, this research shows that a higher frequency measure of ESG performance affects the classification of green stocks in a way that has a non-trivial impact on portfolio returns.

This research also relates to the body of literature that discusses the issues associated with ESG data. Much of the literature to date have relied upon ESG ratings supplied by ratings

providers such as MSCI, Asset 4 by Refinitiv (previously Thompson Reuters), Sustainalytics, or S&P Global, to name a few. A pertinent issue with these traditional measures of ESG performance is that they lack transparency, both in the methodology regarding their construction, and timely reflection of current events.² Additionally, qualitative assessments by ESG rating providers typically occur only annually or when a significant event warrants an out-of-cycle review. The low frequency of revision means that the data is often backward-looking and outdated by the time it reaches investors. This has implications for market efficiency, where investors are unable to act upon, or ignore, mispricing signals due to preferences for ESG (Cao et al., 2023).

Importantly, this research addresses this dilemma by considering sentiment data as an alternative measure of ESG, that are higher frequency and offer a dynamic perspective of ESG (see In et al., 2019; Taleb et al., 2020; Hughes et al., 2021; Sorensen et al., 2022). We therefore add to the burgeoning literature utilising sentiment data for ESG analysis. Advancements in Natural Language Processing (NLP) for example, have led to an increase in research that utilises sentiment datasets to investigate the influence of ESG sentiment on stock returns (Cui and Docherty, 2020; Serafeim, 2020; Serafeim and Yoon, 2022), or to explore its benefits in a portfolio setting (Taleb et al., 2020). Therefore, we join a growing body of researchers and practitioners embracing alternative data to supplement measures of ESG performance with a higher frequency alternative.

4.3 Data

This analysis uses data from three sources: ESG ratings, ESG sentiment scores, and stock market data. The ESG ratings data are obtained from MSCI and proxy the traditional low-frequency measure of ESG performance. ESG sentiment data are obtained from Refinitiv Marketpsych ESG Analytics (RMEA) and proxy the alternative high-frequency measure of ESG performance. Stock market data are obtained from Datastream and Wharton Research Data Services and are used to compute the green minus brown portfolio returns. What follows is a description of the MSCI and RMEA datasets, pre-processing procedures applied, and a description of the greenness scores used in this analysis,

²Issues with scope and methodology of measurement leading to divergence in ratings between providers have been well documented (see Chatterji et al., 2016; Kotsantonis and Serafeim, 2019; Berg et al., 2022).

4.3.1 Traditional ESG

MSCI (previously KLD Research and Analytics) is considered to be the worlds largest ESG ratings agency (Eccles et al., 2020), providing ratings for more than 8,500 companies globally and used by more than 1,700 clients world-wide.³ MSCI generates its ratings predominantly via qualitative processes employing more than 200 analysts to extract insights from a variety of sources. Ratings are typically updated at least annually.⁴

One advantage of MSCI data is its segregation into environmental, social, and governance components (pillar scores) without industry adjustment. While industry adjustment of ratings is often used by MSCI and other ratings providers to reflect a company’s ESG performance relative to its industry peers, it creates a situation where a heavily polluting company can be considered “green” because it pollutes less than its peers. Without industry adjustment, a company is judged on its absolute performance. In this context, a heavily polluting company would be considered to be “brown”.

The MSCI pillar scores (P_score) range from 0 to 10 and measure a company’s weighted-average score across key issues related to each pillar. These scores assess a company’s exposure and resilience to ESG risks. Refer to Table A.3.7 in Appendix A.3 for a summary of the 37 key issues identified by MSCI as financially relevant to ESG performance and their categorisation under each pillar. In addition to the P_score , MSCI provides pillar weights P_weight , which range from 0 to 100. These weights indicate the relevance of each pillar to a company’s industry relative to other pillars. The weights take into account both the contribution of the industry (relative to all others) to environmental or social impact, and the timeline within which the risk or opportunity for companies is expected to materialise. Thus, pillar weights can be seen as a proxy for materiality. Typically, companies within the same industry have similar pillar weights. Importantly, the weights are determined via qualitative processes in accordance with MSCI methodologies and are reviewed annually.

4.3.2 Sentiment ESG

RMEA is a commercial database that relies upon a state of the art NLP engine to analyse textual data contained in news and social media to extract sentiment and volume of discussion on environmental, social, and governance themed content in real time. An important distinction be-

³Accessed at <https://www.msci.com/sustainable-investing/esg-ratings> on 7 January 2025.

⁴Recently, MSCI began to incorporate machine learning and natural language processing into its methodology to improve the timeliness and precision of data collection. During the sample period over which this research was conducted however, ratings were still only updated annually.

tween the RMEA scores and traditional ESG ratings is that the NLP engines deliberately avoid articles or references to a company’s own documents, press-releases and filings. This external perspective of a company’s sustainability characteristics and the frequency with which the scores can be generated have a few notable benefits. First, by excluding company generated content, it avoids the potential for a company to influence a positive outcome in an ESG performance assessment either through greenwashing (Szabo and Webster, 2019) or resource allocation (Drempetic et al., 2020). Second, the systematic manner in which the data is obtained means that less subjectivity is injected throughout the assessment process (Hughes et al., 2021). Finally, it means that the ESG performance for a company can be assessed and updated almost in real-time, capturing changes in a company’s sustainability profile as and when it happens, rather than waiting months for the changes to be reflected in traditional ratings, improving transparency to investors. This final point is central to our hypothesis that the observed difference between expected and realised returns may be related to a misclassification of stocks in the respective green and brown portfolios.

The RMEA data consists of sentiment (*ESG*, *Controversy*), and attention (*Buzz*) variables across ten ESG categories: *emissions*, *environmentalInnovation*, *resourceUse*, *community*, *humanRights*, *product*, *workforce*, *cSRStratgey*, *management*, and *shareholders*. In total, there are 29 variables to consider. The RMEA *ESG* scores capture both positive and negative sentiment relating to an ESG topic. They range between -1 and 1 and are positive in their tonality, meaning a higher score is subjectively positive. The *Controversy* scores capture only sentiment relating to ESG controversies. They range between 0 and 1 and are negative in their tonality. The *Buzz* variable is an indication of the volume and intensity regarding discussion on an ESG topic for a company. *Buzz* range between 0 and inf. The data can be decomposed by media type (i.e. *News* only or *Social* only), or is available as a combination of sources (*News_Social*). The data is available at 1-minute, 1-hour, and daily frequencies. This research utilises the data obtained from the combined media set at 1-minute frequencies.

Due to the granular nature of the data, a number of steps are required to compute scores that are comparable to MSCI. First, the *ESG* and *Controversy* scores are combined to create a single *Sent* variable. Next, the *Sent* and *Buzz* variables are aggregated from 1-minute observations to a daily frequency. The aggregation window is selected between 09:35 on day t to 09:25 on day $t-1$ to include overnight and pre-market sentiment into the daily measure. Observations in the 5-minutes following and preceding market open were excluded to avoid the effects of noise associated with the opening session. Finally, pillar scores are computed for the *Sent*

variables as the *Buzz* weighted-average, and for the *Buzz* variable as the sum, of category scores belonging to each pillar. Details of the above steps are provided in Section A.3.2 of Appendix A.3.

4.3.3 Breaking Buzz! A measure of materiality

When constructing a measure to determine the greenness of a company, such as in Pástor et al. (2022), the weight, or materiality of the ESG performance score plays a critical role. For example, two companies from different industries may have similar score values however, their environmental impacts may differ significantly, thereby altering the relative importance of the score when materiality weights are interacted with the score. Table 4.1, presents an example of how the application of materiality weights alters the relative importance of scores with similar values. In this example, the interaction of the ESG score with the materiality weight implies that less consideration should be given to Best Buy because the impact to the environment is lower than for Exxon Mobile. However, it may not be consistent with the intended representation and additional adjustment may be required. In the example provided by Pástor et al. (2022), the interaction of the score with the weight represents that Best Buy is “greener” than Exxon Mobile. To achieve this representation, they propose a greenness measure which we describe in the next section (see Section 4.3.4).

TABLE 4.1: **Impact of materiality weights.** Example of how materiality weights can alter the performance measure and change the relative greenness between two companies: *Best Buy* and *Exxon Mobile*. The performance measure and materiality weight for the environmental pillar are provided by MSCI as of December 2019.

Company	E_score	E_weight (%)	$E_score \times E_weight$ (%)
Best Buy	4.1	0.11	0.45
Exxon Mobile	4.2	0.48	2.02

Unlike for MSCI, materiality weight is not explicitly provided for in the RMEA dataset. When comparing the relevance of the P_Sent measure between companies, materiality therefore needs to be inferred. One approach would be to simply use the materiality weights from a traditional ratings provider, however, there are issues that make this application unsuitable. For one, as previously discussed, the data origins and methodologies are fundamentally different between the two measures. For the traditional measure, determinations of the score and its materiality are based on large quantities of data combined with expert knowledge and qualitative frameworks. Moreover, traditional measures frame materiality of an issue cross-sectionally, at a single point in time. The RMEA sentiment measures on the other hand are of a time-series nature. They are

derived frequently from smaller pieces of information (i.e. a news article or social media post), that over time paints a picture of how the public feels about a company’s activities relating to an ESG issue. However, because discussion occurs at different speeds and intensities for individual companies, it is difficult to place the discussion at any one time in context of its industry peers or the broader market, and therefore difficult to apply a meaningful cross-sectional comparison.

The question then is how to derive materiality from such a measure? If we proxy the level of media attention received on a topic for the level of importance the public places on that topic, then we can consider materiality in context of the degree of media attention received. However on its own, the level cannot indicate whether the media attention received in time period t is greater or lower than in time period $t + 1$. Thus materiality with this measure must also be considered relative to its own history. We propose to compute materiality for company j at the end of month t as:

$$\omega_{j,t} = \frac{\log Buzz_{j,t}}{\log Buzz_{j,t-1:t-(k \times 30)}}, \quad (4.1)$$

where $\log Buzz_{j,t}$ is the average level of media attention received in the current month computed as $\frac{1}{30} \sum_{i=1}^{30} \log Buzz_i$ from daily $Buzz$ and includes weekends and public holidays. In the denominator, $\log Buzz_{j,t-1:t-(k \times 30)}$ is the average level of media attention estimated over the prior k months excluding the current month. It is computed as $\frac{1}{k \times 30} \sum_{i=30+1}^{30(1+k)} \log Buzz_i$ also from daily $Buzz$. We choose $k=3$ for the main results as we consider 3-months to be a good balance between recency and noise. In robustness tests, we vary the value of k , and find little difference in the results. The materiality measure indicates whether the attention received in the current month is abnormally high or low relative to its recent history. For example, $\omega_{j,t}=6$ indicates that the current month’s $Buzz$ is exponentially greater than the average $Buzz$ over the previous k months by a factor of 6, and is an indication that the public is excited or agitated about a company’s activities relating to the topic.

Figure 4.1 plots the weights computed for a sample of 995 US based companies on media attention received in the environmental pillar ranked from highest to lowest. We observe an asymmetry in the weights computed where abnormally high attention (relative to it prior history) is given a greater weight compared with if the attention is lower. In the case where symmetry is required, we suggest applying an affine transformation that preserves the order of the measure.

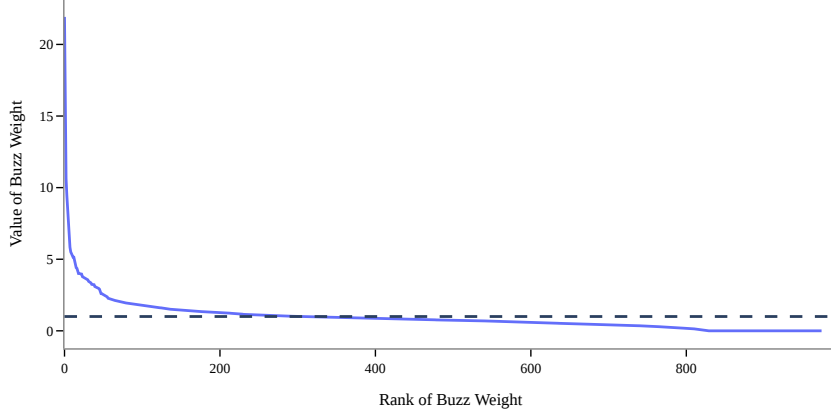


FIGURE 4.1: **Materiality from media attention.** The figure plots the materiality weights computed in Eqn 4.1 for a sample of 995 US based companies on the environmental pillar as of 31 December 2021. Materiality weights are ranked from highest to lowest and presented in descending order.

4.3.4 Measuring greenness

To compute the greenness score for the traditional measure, this analysis follows the methodology of Pástor et al. (2022). The unadjusted greenness scores for pillar P are computed for company j at the beginning of the month t as:

$$G_{P,j,t}^{PST} = -(10 - P_score_{j,t-1}) \times \frac{P_weight_{j,t-1}}{100}, \quad (4.2)$$

where P_score and P_weight refers to the MSCI environmental, social, or governance pillar score and pillar weight respectively. The quantity $10 - P_score$ measures the distance the P_score is from the perfect score of 10. In this case, it is a measure of a company’s “brownness”. The product $(10 - P_score_{j,t-1}) \times \frac{P_weight_{j,t-1}}{100}$ measures the interaction of the brownness score with how large the pillar impacts are for the industry’s typical company. The initial minus sign converts the score from brownness to greenness, where a more negative score is subjectively brown.

The score is then adjusted by the cross-sectional value-weighted average of $G_{P,j,t-1}^{PST}$ across all companies:

$$g_{P,j,t}^{PST} = G_{P,j,t}^{PST} - \overline{G_{P,t}^{PST}}, \quad (4.3)$$

Since $\overline{G_{P,t}^{PST}}$ represents the market portfolio, $g_{P,j,t}^{PST}$ measures the company’s greenness relative to the market portfolio.

To form the greenness score for the sentiment measure, the materiality weight $\omega_{j,t-1}$ computed

in Eqn 4.1 is interacted with the sign of average sentiment in the previous month:

$$g_{P,j,t} = \text{sign}(\text{Sent}_{P,j,t-1}) \times \omega_{P,j,t-1}, \quad (4.4)$$

The sign, rather than the value of average sentiment is used so the intensity of $\omega_{j,t-1}$ is not neutralised. As the number of participants to a discussion increases, so to does the range of opinion. Unless there is strong consensus amongst the group, disagreement will most likely result in a sentiment value that tends towards 0. For the sentiment greenness score, a strong materiality measure may be weakened by differences in opinion, and obscures what is most important, that is the direction of sentiment. Further details, including plots showing the relationship between *Sent* and *Buzz* are provided in Section A.3.3 of Appendix A.3. Figure 4.2 plots the sentiment greenness score for the environmental pillar, $g_{E,j,t}$, as at 31 December 2021 for a sample of 995 companies.

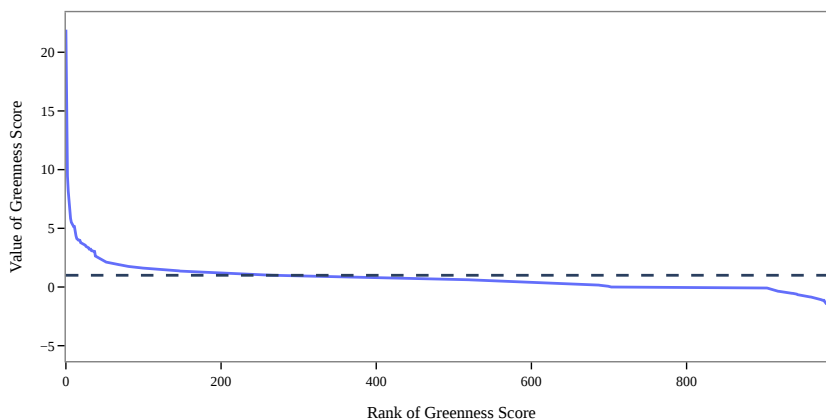


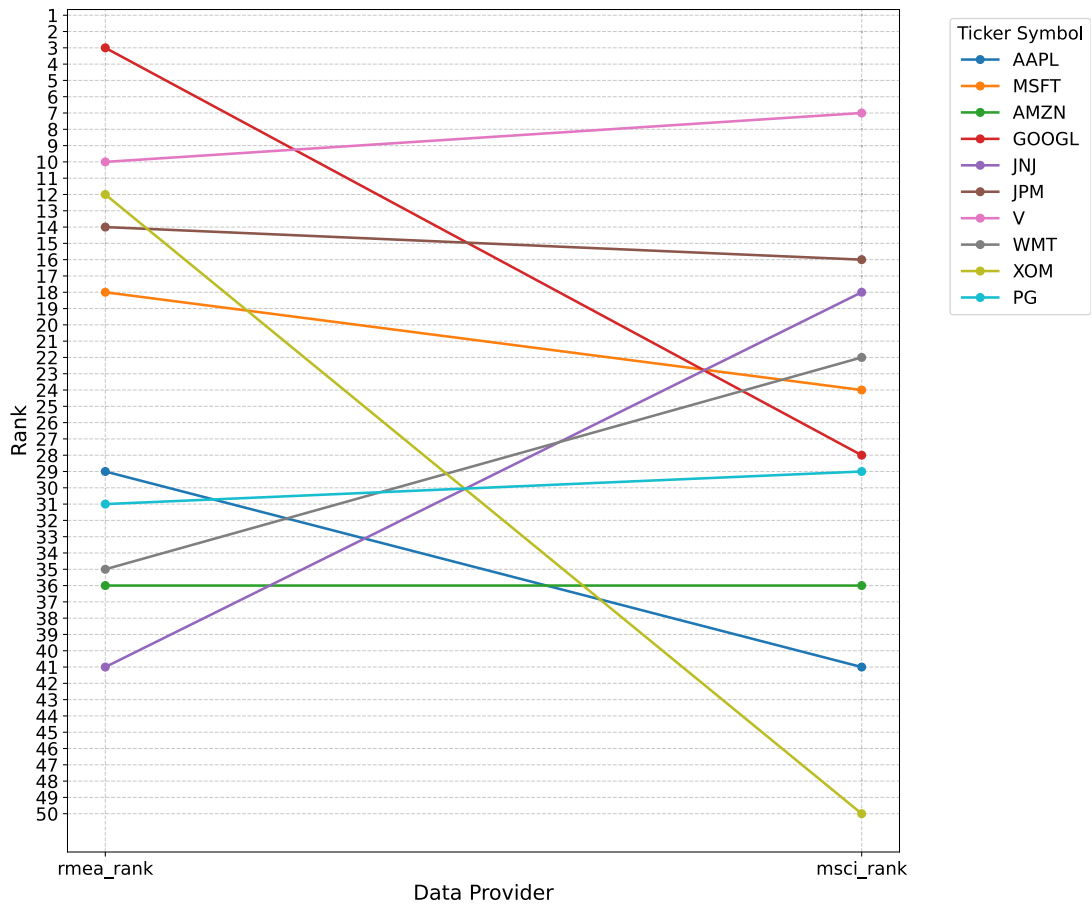
FIGURE 4.2: **Sentiment-based greenness measure - Environmental pillar.** The figure plots the sentiment-based greenness score computed for this analysis for a sample of 995 US based companies on the environmental pillar as of 31 December 2021. The greenness score is computed per Eqn 4.4 as the interaction of the Breaking Buzz! materiality weight and $\text{sign}(\text{Sent})$. The greenness scores are ranked from highest to lowest and presented in descending order.

Interestingly, there is a minor asymmetry in the environmental sentiment-based greenness scores implying a positive bias in the sentiment for many of the companies during this time. This is contrary to the commonly held view that negative news receives greater levels of attention (see Tetlock, 2007; Arratia et al., 2021). Contrasting against the social and governance pillars (presented in Figure A.3.2 in Section A.3.4 of the appendix) it appears to be an anomaly specific to the environmental pillar.

Finally, the sentiment-greenness score ($g_{P,j,t}$) and the traditional-greenness score ($g_{P,j,t}^{PST}$) are evaluated for similarity in their rankings. In the context of conducting a portfolio sort (as

performed to form the GMB portfolios in the following section) the rankings of these scores are more relevant than their values. If the rankings of the two sets of scores are similar, it can be inferred that the GMB returns will also exhibit similarity. Therefore, for this analysis to be meaningful, there must be a significant difference in the rankings between the two types of greenness scores. Figure 4.3 compares the rankings of the top 50 US companies based on market capitalisation as at December 2019. The LHS ranks the companies based on the $g_{i,t}$ computed from Eqn 4.4 using RMEA data from highest to lowest. The RHS shows the same, but using the $g_{j,t}^{PST}$ score computed from MSCI. In this time period, there are clear differences in the rankings between the two measures. For example, Alphabet Inc. (GOOG) is ranked in the third position based on the $g_{j,t}$ measure, whilst with the $g_{j,t}^{PST}$ measure, it ranked 28th.

FIGURE 4.3: **Ranking difference between RMEA and MSCI.** The figure offers an illustrative comparison of how the rankings may differ between data providers, RMEA (LHS) and MSCI (RHS). Greenness scores are computed from the RMEA sentiment scores ($g_{j,t}$) and MSCI ratings ($g_{j,t}^{PST}$) as at December 2019. $g_{j,t}^{PST}$ is computed per the methodology in Pástor et al. (2022) (Eqn 1). $g_{j,t}$ is computed per Eqn 4.4. For the purpose of the example, the Greenness scores are obtained for the 50 largest US companies by market capitalisation in the sample, and ranked from highest to lowest for each data provider. To aid visualisation, only 10 companies are displayed.



4.4 Methodology

This analysis focuses on the sample of US companies with CRSP share codes of 10 or 11. The MSCI, RMEA and CRSP databases are merged using a combination of CUSIP, ticker and company name. The sample extends from January 2016 to December 2021. Companies with missing monthly data in the MSCI dataset, and missing monthly average sentiment in the RMEA dataset, are excluded from the sample for each pillar. Table 4.2 shows the average greenness scores and number of companies for each pillar in the full sample and by GICS Sector.

TABLE 4.2: **Greenness scores by GICS sector.** This table presents the number of US companies in our sample, the average sentiment-greenness score ($g_{j,t}$), and the average traditional-greenness score ($g_{j,t}^{PST}$) for the Environmental (Columns (1) to (3)), Social (Columns (4) to (6)), and Governance (Columns (7) to (9)) pillars between January 2016 and December 2021.

	Environmental			Social			Governance		
	# Companies (1)	RMEA (2)	MSCI (3)	# Companies (4)	RMEA (5)	MSCI (6)	# Companies (7)	RMEA (8)	MSCI (9)
All	995	0.89	-0.40	1,243	0.65	-0.02	1,198	-0.37	0.14
Communication Services	32	0.72	0.50	47	0.38	-0.33	43	-0.52	-0.64
Consumer Discretionary	152	0.85	-0.24	187	0.60	-0.56	181	-0.46	0.38
Consumer Staples	55	0.87	-0.91	66	0.59	-0.12	66	-0.31	0.63
Energy	47	0.33	-2.11	52	0.37	1.54	51	-0.46	0.12
Financials	134	0.93	0.53	198	0.68	-1.24	184	-0.39	0.21
Health Care	124	0.80	0.74	168	0.66	-0.35	160	-0.52	-0.47
Industrials	196	0.96	-0.47	236	0.69	0.72	230	-0.33	-0.09
Information Technology	139	1.08	-0.37	158	0.80	-0.05	157	-0.28	0.33
Materials	59	0.97	-2.50	70	0.66	1.01	65	-0.27	0.64
Real Estate	8	1.03	-0.60	9	0.63	0.64	9	-0.09	-0.15
Utilities	49	0.99	-1.91	52	0.74	1.70	52	-0.06	0.79

One limitation of the ESG sentiment-based measures is that discussion on ESG issues for a company may not be uniform across the ESG pillars with one or two of the pillars receiving more data than the others. Once companies with missing monthly average data are removed, the environmental pillar records 995 companies with non-missing RMEA and MSCI data. Meanwhile, the social and governance pillar report 1,243 and 1,198 companies respectively. On average, the Information Technology and Real Estate sectors in the environmental pillar experienced greater abnormal *Buzz* with average $g_{i,t}$ scores of 1.08 and 1.03 respectively. We also observe that the sentiment for environmental and social pillars overall is positive for all sectors, whilst the sentiment for the governance pillar is overwhelmingly negative.

To investigate the equity greenium puzzle, value-weighted portfolios of green-minus-brown (GMB) stocks are formed by performing a portfolio sort on the greenness measures discussed in the previous section. The objective is to determine whether a dynamic measure of ESG affects the classification of green and brown stocks substantially from a traditional backward-looking measure. Moreover, it aims to demonstrate that an ESG measure that is better aligned with the

information reflected in stock prices, will result in a realised equity greenium that is neutral or negative, inline with theoretical expectations:

H1: *Sentiment-based measures of ESG performance reduce the equity greenium.*

There is sufficient reason to suggest that the GMB returns for environmental, social, and governance pillars should differ. For example, with climate change being such a prominent issue for investors, it stands to reason that stocks that are viewed to hedge against climate change risks, and therefore closely related to the environmental pillar, would be more susceptible to price action resulting from investor preferences (Engle et al., 2020; Pástor et al., 2022; Ardia et al., 2023). Investor reaction to social issues on the other hand may be more difficult to ascertain given the vagueness of social issues (Dempsey et al., 2011; Ajmal et al., 2018). This leads to the second hypothesis:

H2: *GMB factors show differences across ESG pillars.*

The green and brown portfolios are formed by ranking the monthly greenness scores $g_{P,j,t}$ and $g_{P,j,t}^{PST}$, from highest to lowest. This is performed for each of the E, S and G pillars, and for each month-year of the sample period. The green portfolios consist of stocks with greenness scores in the top third, while the brown portfolios consist of stocks with greenness scores in the bottom third. Portfolios are rebalanced monthly, and portfolio returns are computed as value-weighted returns.⁵ The GMB factor is computed as the monthly return difference between the green and brown portfolios formed from the sentiment-based greenness score ($g_{P,j,t}$). Similarly, the GMB-PST factor is computed as the monthly return difference between the green and brown portfolios formed from the traditional greenness score ($g_{P,j,t}^{PST}$).

To investigate the performance of GMB, two sets of regressions are run. First, as with Pástor et al. (2022), the GMB factor is regressed on common return factors prominent in the asset pricing literature to infer the source or relationship of the GMB factor with the common factors. The common return factors include the three- and five-factor models of Fama and French (1993) and Fama and French (2015), the four-factor model of Carhart (1997), the liquidity factor model of Pástor and Stambaugh (2003), and the q-factor models of Hou et al. (2015) and Hou et al. (2021):

⁵The results from equal-weighted portfolios are also examined in robustness checks.

$$GMB_{P,t} = \alpha + \beta^T \mathbf{F}_t + \epsilon_t, \quad (4.5)$$

where β is a $m \times 1$ vector of factor coefficients \mathbf{F} is a m -dimensional column vector that contains the factors of the prominent asset pricing models outlined above.

Second, the GMB factors are regressed against each other primarily to determine whether one GMB factor exerts any influence on the other. This regression analysis indirectly examines the relationship between traditional and sentiment-based measures of ESG. Despite the substantial differences in the construction of these measures, it is reasonable to anticipate some degree of similarity in green / brown portfolio stock selection and a correlation between the GMB factors, given the similarities in the issues they address.

$$GMB_{P,t} = \alpha + \gamma GMB_{P,t}^{PST} + \epsilon_t, \quad (4.6)$$

$$GMB_{P,t}^{PST} = \alpha + \lambda GMB_{P,t} + \epsilon_t, \quad (4.7)$$

A positive and significant coefficient on the GMB-PST factor, (γ), implies that despite being backwards-looking and slow to update, the traditional measure bears some influence on the dynamic measure that is not obvious when contrasting them directly. Conversely, a positive and significant coefficient on the GMB factor (λ) implies that the returns of the GMB-PST factor may be influenced in part by investor reactions to sentiment relating to ESG issues.

4.5 Empirical Results

4.5.1 GMB performance

Figure 4.4 compares the cumulative returns of the value-weighted GMB factor with the value-weighted GMB-PST factor for the environmental (Panel A), social (Panel B), and governance pillars (Panel C). For completeness, Table 4.3 presents the performance statistics showing the cumulative return, annualised return, annualised standard deviation, and information ratio (IR) of the excess returns of the market portfolio (S&P500), as well as the GMB and GMB-PST factors for environmental, social and governance pillars.

Unlike Pástor et al. (2022), the GMB factor reports only weak outperformance of green stocks relative to brown in the environmental pillar, resulting in a cumulative return of 6.17%

TABLE 4.3: **Performance Statistics - Value weighted.** This table presents some common performance statistics of the excess returns of the market portfolio, and the GMB and GMB-PST factors for the environmental (E), social (S), and governance (G) pillars. The S&P500 is used as the proxy for the market portfolio.

	Mkt-RF	GMB			GMB-PST		
		E	S	G	E	S	G
Cum. Ret	147.81%	6.17%	46.43%	-27.72%	-7.76%	-26.23%	4.84%
Ann. Ret	19.90%	1.21%	7.93%	-6.29%	-1.60%	-5.90%	0.95%
Ann. Std	15.21%	5.06%	8.14%	7.97%	6.22%	6.10%	5.57%
IR	1.12	0.22	0.82	-0.64	-0.19	-0.80	0.17

(1.08% annualised) between May 2016 and December 2021.⁶ This compares with 46.43% (7.07% annualised) for the GMB-PST factor, a difference of 40.25% (5.99% annualised). The factors from the social and governance pillars show negative cumulative GMB factor returns. The social GMB returns -27.72% (-5.65% annualised) and the governance GMB returns -26.23% (-5.30% annualised). In comparison, the social and governance GMB-PST factors return -7.76 (-1.44% annualised) and 4.84% (0.85% annualised), respectively.

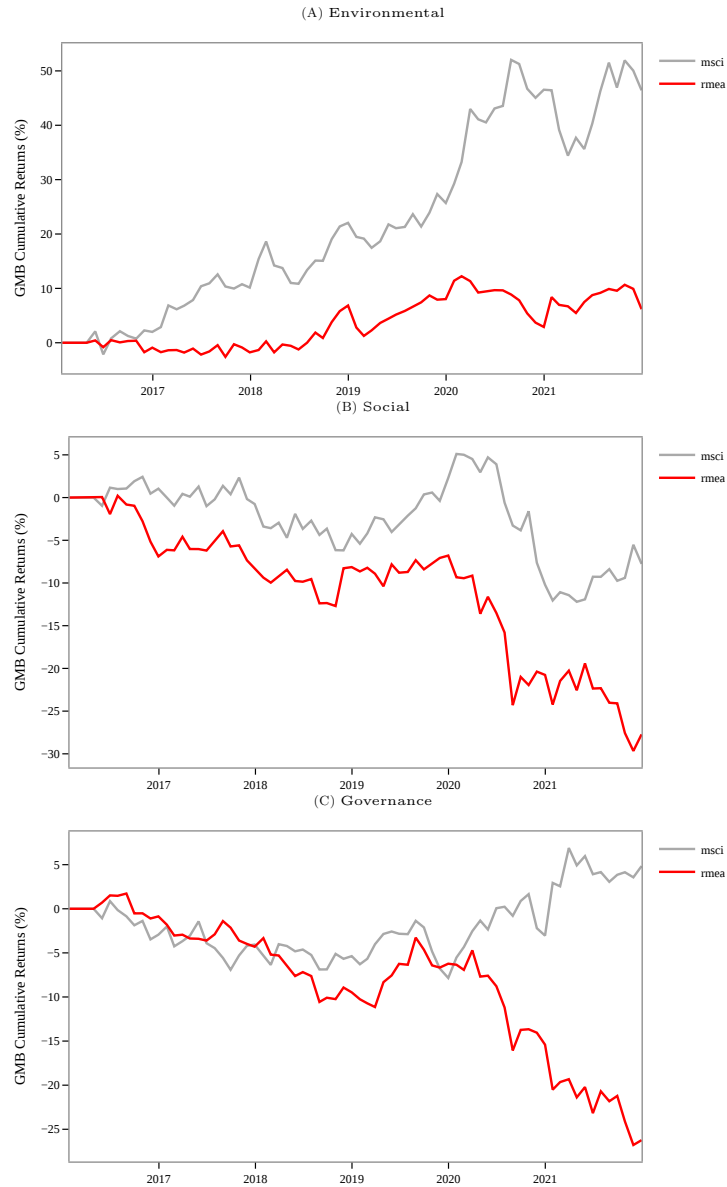
Table 4.4 presents the results of the GMB factor for the environmental pillar regressed against the return factors prominent in the asset pricing literature. The first column presents the monthly return of the GMB portfolio (regression constant). The remaining columns report the results of regressing GMB on the following factor models: three- and five-factor models of Fama and French (1993, 2015); the momentum factor as constructed by those authors, the traded liquidity factor of Pástor and Stambaugh (2003), and the q-factor models of Hou et al. (2015, 2021). For completeness, the regressions were also performed for the GMB-PST factor with the results presented in Table A.3.9 in Appendix A.3. Although our results differ they are economically and statistically consistent with Pástor et al. (2022), and are likely to be due to differences in the composition of our respective samples.

Contrary to the findings of Pástor et al. (2022), this analysis does not confirm the outperformance of green stocks. Moreover it appears that the GMB factor is orthogonal to common market factors. Although positive, the alphas are not statistically significant ranging between 10bps and 23bps. The alpha's t-statistics range between 0.54 and 1.18. The market factor reveals a negative and significant relationship with the GMB factor, however once other factors are accounted for, the significance of this relationship disappears. Similarly, tilts towards other factors, such as size and profitability, are inconsistent across models.

The analysis is repeated for the social (Table 4.5), and the governance pillars (Table 4.6). Similar to the environmental pillar, the alphas for the GMB factor were not statistically sig-

⁶The first four months of our sample were used to compute the Breaking Buzz! metric

FIGURE 4.4: **GMB - Value Weighted.** This figure presents the sustainability factors for Environmental (Panel (A)), Social (Panel (B)), and Governance pillars (Panel (C)). The GMB factor is defined as the returns of the Green portfolio minus the returns of the Brown portfolio between May 2016 and December 2021. The Green (Brown) portfolio are formed of the companies with $g_{i,t}$ scores in the top (bottom) third in a given month-year. The red (grey) line represents the cumulative value-weighted returns of the GMB factor formed from the RMEA (MSCI) scores.



nificant for the social and governance pillars. However, they did exhibit a negative and mostly statistically significant relationship between the GMB and market factors, with a stronger relationship for the social pillar. This consistent relationship across factor models suggests that the GMB factor for social and governance pillars may serve as a useful hedge against market

TABLE 4.4: **Value-weighted GMB performance - Environment.** Monthly time-series regressions are estimated using data from January 2016 to December 2021. The dependent variable is the GMB factor computed as the difference between the value-weighted returns on the green portfolio and brown portfolios formed by the top (bottom) third of stocks ranked by their greenness score in the previous month ($g_{j,t-1}$). Mkt-Rf is the excess market return. SMB and HML are the size and value factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997). LIQ is the traded liquidity factor of Pástor and Stambaugh (2003). RMW and CMA are the profitability and investment factors of Fama and French (2015). ME, I/A, and ROE are the size, investment, and profitability factors of Hou et al. (2015). EG is the expected growth factor of Hou et al. (2021). Returns are in percent per month. Robust t-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
const	0.10 (0.54)	0.22 (1.15)	0.19 (0.90)	0.15 (0.81)	0.17 (0.90)	0.23 (1.18)	0.19 (0.87)	0.16 (0.72)
Mkt-RF		-0.08 (-2.06)	-0.06 (-1.15)	-0.01 (-0.20)	-0.04 (-1.08)	-0.03 (-0.65)	-0.07 (-1.41)	-0.06 (-1.18)
SMB			-0.11 (-1.05)	-0.06 (-0.57)	-0.09 (-0.70)	-0.21 (-2.26)		
HML			0.01 (0.20)	0.09 (1.53)	-0.01 (-0.07)	0.06 (0.81)		
MOM				0.19 (2.31)				
LIQ					-0.05 (-0.54)			
RMW						-0.21 (-2.24)		
CMA						-0.02 (-0.13)		
ME							-0.04 (-0.34)	-0.03 (-0.28)
I/A							-0.03 (-0.21)	0.00 (0.01)
ROE							0.02 (0.45)	-0.00 (-0.02)
EG								0.05 (0.32)
Observations	69	69	69	69	69	69	69	69
R2	0.00	0.06	0.10	0.23	0.11	0.16	0.08	0.08

downturns. The significant exposure to the momentum factor also suggests that GMB factor tilts towards recent winners for all pillars. Again the regressions were performed on the GMB-PST factor for the social and governance pillars (see Tables A.3.10 and A.3.11 in Appendix A.3). It was interesting to observe that unlike the environmental pillar, the results on the GMB-PST factor were consistent with our own. This indicates that the characteristics that drive the equity greenium discovered by Pástor et al., 2022 are unique to the environmental pillar.

These findings are robust when varying the k parameter to 6 and 12 months in the Breaking Buzz! measure (Eqn 4.1).⁷ In other robustness checks, similar results are obtained when the

⁷For robustness k is set to 6 and 12 so that materiality of the average *Buzz* in the current month is determined with respect to average *Buzz* generated over the prior 6 and 12 months respectively.

TABLE 4.5: **Value-weighted GMB performance - Social.** We estimate monthly time-series regressions using data from January 2016 to December 2021. The dependent variable is the GMB factor computed as the difference between the value-weighted returns on the green portfolio and brown portfolios formed by the top (bottom) third of stocks ranked by their greenness score in the previous month ($g_{j,t-1}$). Mkt-Rf is the excess market return. SMB and HML are the size and value factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997). LIQ is the traded liquidity factor of Pástor and Stambaugh (2003). RMW and CMA are the profitability and investment factors of Fama and French (2015). ME, I/A, and ROE are the size, investment, and profitability factors of Hou et al. (2015). EG is the expected growth factor of Hou et al. (2021). Returns are in percent per month. Robust t-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
const	-0.44 (-1.56)	-0.23 (-0.93)	-0.16 (-0.59)	-0.12 (-0.46)	-0.17 (-0.63)	-0.12 (-0.44)	-0.15 (-0.56)	-0.16 (-0.51)
Mkt-RF		-0.15 (-2.03)	-0.18 (-2.22)	-0.23 (-2.86)	-0.17 (-2.30)	-0.18 (-2.31)	-0.18 (-2.07)	-0.17 (-2.03)
SMB			0.06 (0.54)	0.01 (0.09)	0.08 (0.55)	0.02 (0.19)		
HML			0.09 (1.04)	-0.00 (-0.01)	0.07 (0.84)	0.14 (1.36)		
MOM				-0.20 (-2.30)				
LIQ					-0.04 (-0.42)			
RMW						-0.10 (-0.48)		
CMA						-0.14 (-0.69)		
ME							0.02 (0.14)	0.02 (0.14)
I/A							0.07 (0.42)	0.07 (0.34)
ROE							-0.12 (-1.23)	-0.13 (-0.90)
EG								0.01 (0.04)
Observations	69	69	69	69	69	69	69	69
R2	0.00	0.08	0.11	0.17	0.11	0.12	0.11	0.11

analysis is performed on equal-weighted GMB and GMB-PST portfolios. Once again, alphas on the equal-weighted GMB factor for the environmental, social, and governance pillars do not differ significantly from zero. In the equal-weighted GMB factor, all three pillars also appear to tilt towards large companies, which was not evident from the value-weighted portfolios. This may be an outcome of the GMB portfolio construction as it is observed that unlike the value-weighted portfolios, the equal-weighted portfolios no longer indicate exposure to the momentum factor and exposure to the market factor is reduced for the GMB factor for all pillars. See Section A.3.5.2 of the Appendix A.3 for a full set of results relating to the robustness checks outlined above.

TABLE 4.6: **Value-weighted GMB performance - Governance.** We estimate monthly time-series regressions using data from January 2016 to December 2021. The dependent variable is the GMB factor computed as the difference between the value-weighted returns on the green portfolio and brown portfolios formed by the top (bottom) third of stocks ranked by their greenness score in the previous month ($g_{j,t-1}$). Mkt-Rf is the excess market return. SMB and HML are the size and value factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997). LIQ is the traded liquidity factor of Pástor and Stambaugh (2003). RMW and CMA are the profitability and investment factors of Fama and French (2015). ME, I/A, and ROE are the size, investment, and profitability factors of Hou et al. (2015). EG is the expected growth factor of Hou et al. (2021). Returns are in percent per month. Robust t-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
const	-0.42 (-1.96)	-0.25 (-1.17)	-0.24 (-1.13)	-0.21 (-1.01)	-0.24 (-1.17)	-0.20 (-1.01)	-0.27 (-1.32)	-0.25 (-1.06)
Mkt-RF		-0.12 (-2.82)	-0.10 (-1.73)	-0.14 (-2.47)	-0.10 (-1.81)	-0.12 (-1.90)	-0.09 (-1.46)	-0.10 (-1.51)
SMB			-0.14 (-1.31)	-0.18 (-1.80)	-0.13 (-1.01)	-0.16 (-1.56)		
HML			0.09 (1.69)	0.02 (0.39)	0.09 (1.40)	0.15 (1.79)		
MOM				-0.16 (-2.01)				
LIQ					-0.01 (-0.16)			
RMW						-0.04 (-0.26)		
CMA						-0.16 (-0.95)		
ME							-0.16 (-1.40)	-0.17 (-1.43)
I/A							0.05 (0.45)	0.02 (0.14)
ROE							-0.04 (-0.50)	-0.01 (-0.12)
EG								-0.05 (-0.38)
Observations	69	69	69	69	69	69	69	69
R2	0.00	0.09	0.14	0.21	0.14	0.16	0.13	0.14

4.5.2 Relationship between sentiment and traditional measures

This analysis also tests the proposition that the GMB factors affect each other, and provides evidence of a significant bi-directional impact between the contemporaneous value-weighted GMB factors for the environmental pillar only. Table 4.7 presents the regression results, with GMB as the dependent variable in Panel A and GMB-PST as the dependent variable in Panel B. The results for the environmental pillar are shown in columns (1) and (2), the social pillar in columns (3) and (4), and the governance pillar in columns (5) and (6). Both sets of regressions control for the influence of excess market returns on the factors, as seen in columns (2), (4), and (6). In these regression specifications, only the environmental pillar displays positive and significant exposure

to the GMB factors. For instance, the results in column (1) of Panel A reveal that GMB-PST contributes 22 basis points to the returns of the GMB factor, while the results in column (1) of Panel B indicate that GMB contributes 57 basis points to the returns of the GMB-PST factor. This finding seems to suggest a commonality specific to the environmental pillar from traditional measures that persists to the sentiment measure. For example, one possible explanation may be a cross-over between the price impacts from investor flows moving towards “green” assets based on traditional ESG ratings, and investor reaction to positive sentiment which would be picked up from the Breaking Buzz! measure.

TABLE 4.7: **GMB factor regression.** Monthly time-series regressions are estimated using data from January 2016 to December 2021. Panel A presents the regression where the dependent variable is the value-weighted GMB return and Panel B presents the regression where the dependent variable is the value-weighted GMB-PST return. Mkt-Rf is the excess market return. Robust t-statistics are in parentheses.

Panel A - Dependent variable GMB						
	Environment		Social		Governance	
	(1)	(2)	(3)	(4)	(5)	(6)
const	-0.03 (-0.17)	0.08 (0.41)	-0.44 (-1.56)	-0.24 (-0.92)	-0.44 (-2.04)	-0.24 (-1.21)
GMB-PST	0.22 (2.95)	0.2 (2.65)	0.08 (0.43)	-0.02 (-0.10)	0.09 (0.41)	-0.03 (-0.13)
Mkt-RF		-0.07 (-1.54)		-0.15 (-2.22)		-0.13 (-2.48)
Observations	68	68	68	68	68	68
R2	0.12	0.16	0	0.08	0.01	0.09
Panel B - Dependent variable GMB-PST						
	Environment		Social		Governance	
	(1)	(2)	(3)	(4)	(5)	(6)
const	0.53 (1.92)	0.58 (1.67)	-0.08 (-0.36)	0.05 (0.24)	0.12 (0.65)	0.27 (1.59)
GMB	0.57 (3.04)	0.54 (2.49)	0.05 (0.47)	-0.01 (-0.10)	0.08 (0.43)	-0.02 (-0.13)
Mkt-RF		-0.03 (-0.30)		-0.11 (-1.58)		-0.14 (-2.75)
Observations	68	68	68	68	68	68
R2	0.12	0.13	0	0.07	0.01	0.13

4.6 Discussion

This analysis finds that a greatly reduced equity greenium is obtained when a measure of ESG performance that is more reflective of the current environment is used to classify stocks as green or brown. Our results are consistent with the findings of Hong and Kacperczyk (2009) and Bolton and Kacperczyk (2021), who link brown assets with higher risk adjusted returns. This in

turn, adds to the growing empirical evidence supporting the notion that investors are willing to sacrifice returns for the perception of doing good.

Relating this work to Pástor et al. (2022), we make a bold assertion - that the extraordinary positive greenium they observe, may in part be attributed to using an outdated measure to classify stocks as green or brown. This research does not aim to detract from their significant and ground-breaking revelations linking the recent outperformance of green stocks to climate shocks.

⁸ On the contrary, we propose that if they had allowed for the ESG performance measure to be reflective of current events, the neutral equity greenium they observed after controlling for climate shock, should be lower than they predicted.

This research also finds negative and significant exposure to the market factor, but only for the GMB factor formed from social and governance sentiment indicators. This implies, where detected, the sentiment-based GMB factor has the potential to act as a hedge during market downturns, but also reveals subtle, yet notable differences in the GMB factor that are sensitive to the topics generating the sentiment. This observation is similar to observations in previous chapters (see Chapters 2 and 3) that suggest sentiment related to the environmental issues are different to sentiment relating to social or governance issues. Moreover, it reinforces the view that the outcomes of analysis based on one of the E, S or G pillars cannot and should not automatically translate to the other pillars.

An important contribution of this research is the introduction of the Breaking Buzz! metric which measures the timeliness and materiality of ESG-related public opinion. The *Buzz* metric provides an indication of the level of media attention that a company receives concerning ESG activities discussed in news and social media. However, there are a number of issues with using this measure as a proxy for materiality. On its own, the *Buzz* variable does not show whether it is larger or smaller than at any other time. Moreover, *Buzz* cannot be compared relative to other companies due to the different speeds of discussion and coverage in the media. Thus, the critical innovation of the Breaking Buzz! metric lies in normalising the current month's average *Buzz* by its own recent history. This normalisation allows for materiality to be evaluated in context of its own history and facilitates comparison in the cross-section.

A limitation of Breaking Buzz! metric however, is that it does not account for qualitative determinations of materiality, that is materiality of ESG issues that are determined by expert analysis. However, providing a measure of materiality informed by data alone only broadens the suite of data available to investors, facilitating sustainable investment decisions. Furthermore,

⁸Of which there is also ample support for in the literature (see Brandon et al., 2020; Ardia et al., 2023).

as *Buzz* is independent of subjectivity biases it enhances the transparency of ESG performance measures. For instance, if a company is rated highly but recent sentiment is negative and Breaking Buzz! indicates above-normal attention, this may serve as an early warning indicator of potential issues. In this sense, the application of the Breaking Buzz! metric is similar to how Serafeim (2020) incorporate sentiment in a trading strategy. Breaking Buzz! however adds to the application by incorporating materiality of sentiment.

It could also be argued that a sentiment measure is not philosophically aligned with ESG, given that development towards sustainability is an evolution that occurs over longer time scales, and that the sentiment measure is too noisy to provide a meaningful indication of a company's ESG performance. We disagree with this view and highlight that sentiment has the potential to reveal issues with a company long before it is captured by traditional measures. Additionally, taking the average sentiment over a longer time frames (e.g. 1 month) smooths the sentiment signal, and addresses the asynchronicity and seasonality issues typically present in sentiment datasets (see Gan et al., 2020).

We now consider other explanations for our results and open opportunities for further research. On the face of it, our findings could be at odds with the research that claims green stocks outperform brown because of demand induced price pressures from investors. One way to reconcile our findings with these observations is to consider that our GMB factor could instead be reflective of the “negativity effect hypothesis” described by Akhtar et al. (2012). Under this hypothesis, negative news has greater impact on stock prices than positive news. Stocks that have seen price declines due to negative sentiment should (according to finance theory) generate higher future expected returns. Per our ranking methodology, these stocks will be classified as brown. Conversely, stocks that report positive sentiment will be classified as green, and generate lower future expected returns. However because investors react less (or not at all) to positive news, the price impact to positive sentiment is lower, leading to a perceived outperformance of brown stocks. In other words, our results may be reflective of investor behaviour described in the sentiment literature, as opposed to investors willingly giving up returns for sustainability. This is an important consideration and future research is warranted to dissect the returns of a portfolio formed using the Breaking Buzz! measure to confirm the source of returns. One such extension may involve contrasting the GMB factor against innovations in climate change indices per Pástor et al. (2022) and Ardia et al. (2023).

It is also possible that biases in the sentiment data, or the short sample period could be a contributing factor for our results. For example, positive average values detected in Table 4.2 for

the environmental pillar might explain its positive equity greenium. With much of the focus of ESG being directed towards emissions and climate risk, it is plausible to suggest that investors are gravitating towards companies whose environmental activities are discussed positively in the media. This explanation is consistent with the argument put forward by Pástor et al. (2022). This may also explain why positive equity greenium is detected only for the environmental pillar and not for either the social or governance pillars in the GMB and GMB-PST regressions. Similarly, due to the short time frame of our analysis, our results might be picking up regime-like anomalies. For example, the COVID period covers a significant portion of our sample, and our results may have been influenced by market activity during that time. Alternatively, our analysis ends just as interest rates start rising in February 2022, and it is possible that our results are an artefact of a low-interest rate environment. As such, this research will benefit by extending the sample period of the analysis to include different market regimes. It would also benefit from further analysis to examine if biases in the sentiment data affect stock prices or influence investor behaviour.

To the best of our knowledge, this analysis is the first of its kind. That is, to first use sentiment as a proxy for ESG performance, then apply this measure to categorise stocks into green and brown portfolios, and finally contrast the results with those generated using a traditional measure of ESG performance. The results of our research reveal the limitations of using traditional measures of ESG performance and adds to the discourse that exists regarding ESG data. Much of the discourse however relates to inconsistencies between traditional ESG measures, that until revealed by Chatterji et al. (2016), Kotsantonis and Serafeim (2019), and Berg et al. (2022), were assumed to be similar. Research involving ESG sentiment data is still in its infancy and it is yet to be determined whether similar issues are detected in ESG sentiment measures. Thus a useful contribution to the literature focusing on ESG data would be to extend the analysis of Berg et al. (2022) to sentiment data. In this analysis, we have also only focused on sentiment combined from news and social media sources. Yet, the discourse of these two media types are vastly different (Sun et al., 2016; Gan et al., 2020). Further analysis could decompose the Breaking Buzz! signal into its media components and investigate whether one type of media has a greater influence on investor behaviour than the other. Additionally, this analysis is based only on one type of proxy for high frequency ESG performance. Future research therefore may validate or expand our findings by applying our methodology to ESG sentiment from a different provider or, explore alternative high-frequency datasets. Future research could also extend this framework to other markets.

4.7 Conclusion

This chapter investigates the equity greenium puzzle, hypothesising that the observed outperformance of green portfolios may be partially attributed to the misclassification of stocks into green and brown categories due to the backward-looking nature of traditional ESG ratings. By employing a higher-frequency measure of ESG performance derived from sentiment in news and social media, we construct a value-weighted green-minus-brown (GMB) factor and compare it with the GMB factor formed using traditional ESG ratings (GMB-PST). Our findings reveal that the sentiment-based GMB factor consistently delivers lower cumulative returns across the environmental, social, and governance pillars compared to GMB-PST, indicating that delays in ESG classification could significantly influence the greenium. Furthermore, we detect negative and significant exposures to the market factor, highlighting the potential of the sentiment based GMB factor as a hedging tool during market downturns.

These results underscore the limitations of traditional ESG metrics in capturing real-time sustainability performance and their potential to distort portfolio dynamics. This study contributes to the ongoing discourse on ESG measurement by introducing the “Breaking Buzz!” metric, which accounts for the timeliness and materiality of public perception. This work not only offers a novel approach to understanding ESG dynamics but also has practical implications for investors and policymakers seeking to integrate sustainability into financial decision-making. For example, investors may use this new metric as an early warning signal to changes in a company’s sustainability profile, or policymakers may refer to the findings and require the inclusion of higher frequency sustainability measures in future analysis. Future research could extend this framework to other markets and explore alternative high-frequency datasets to validate and expand these findings.

Chapter 5

Conclusion

This thesis addresses a pertinent issue in financial markets central to the recent trend towards environmental, social, and governance (ESG) investing: how to measure ESG? In this thesis, I discuss how ESG sentiment, an alternative way to capture ESG performance, can enhance decision-making for investors and policymakers by providing timely insights into the impact of ESG on asset pricing. Importantly, it reveals the limitations of existing ESG metrics that have real-world implications.

In introducing this thesis, we pose the question: “How can sentiment address the limitations of traditional ESG ratings, and enhance our understanding of risk and return in financial markets”. This question is answered across three chapters. Chapter 2 introduces the sentiment data used throughout this analysis. It discusses the main issues plaguing traditional measures of ESG and how sentiment data addresses them, primarily through increased timeliness, transparency, and objectivity. Chapter 3 reveals that uncertainty in ESG contributes significantly and economically to stock price volatility and that including ESG sentiment variables can significantly improve out-of-sample forecasts. Chapter 4 investigates the “equity greenium” puzzle and contrasts the difference in portfolio dynamic between fast and slow measures of ESG. Importantly, it reveals that a delay in ESG classification can significantly influence the equity greenium. Additionally, it introduces a novel metric “Breaking Buzz!” that offers a practical tool for researchers and practitioners to integrate ESG sentiment into their analysis and decision-making.

This thesis significantly contributes to the evolving discourse on ESG by integrating sentiment-driven approaches into sustainable finance. It adds to the growing literature examining the benefits of using alternative datasets to enrich our understanding of investor behaviours related to

ESG and the impact this has on asset pricing. We also contribute to the behavioural finance literature by decomposing sentiment into distinct discussion groups and by media type. We reveal differences in the communication channels preferred by investors and demonstrate that not all sentiments are the same.

In summary, this thesis demonstrates that ESG sentiment can serve as a dynamic and effective alternative to traditional measures of ESG, and opens opportunities for further research. We hope that this thesis serves as a guide for future researchers and practitioners by providing novel tools and instructions for using ESG sentiment data in their analysis and investment processes.

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Chapter A

Appendix

A.1 Appendix for Chapter 2

A.1.1 RMEA variables

TABLE A.1.1: **RMEA variables.** This table lists the RMA scores and their corresponding E, S and G related categories available in the Refinitiv Marketpsych ESG Analytics Advanced Package. Panel A presents the RMA Sentiment scores which capture positive and negative sentiment, and are bounded between -1 and 1. Panel B presents the RMA Controversy scores which capture negative sentiment only, and are bounded between 0 and 1. Panel C present *Buzz* which is a measure of media attention and are bounded from below at 0.

Panel A: Sentiment Scores, range (-1, 1)					
Environmental		Social		Governance	
Category	RMA Score	Category	RMA Score	Category	RMA Score
Emissions	climatePolicy airborneEmissionsImprovement carbonEmissionsImprovement recycling environmentalInvestment renewableEnergy renewableEnergyPolicy pollutionImprovement	Community	trust publicHealthSupport charity accessAffordability	Management	managementSentiment managementDiversity qualityMgmtSystems managementTrust
Environmental Innovation	sustainabilityImprovement sustainableInnovation sustainablePackaging	Human Rights	humanRightsEfforts productSentiment privacyEfforts innovation	Shareholders	antiTakeoverDevices accountingSentiment
Resource Use	supplyChainSustainability energyEfficiencyEfforts	Product	customerSatisfaction workplaceSentiment workplaceSafetyEfforts workplaceDevelopment diversityEfforts benefits workLifeBalance wageFairness	CSRStrategy	cSRActivities
		Workforce			
Panel B: Controversy Scores, range (0, 1)					
Environmental		Social		Governance	
Category	RMA Score	Category	RMA Score	Category	RMA Score
Emissions	airborneEmissionsControversy carbonEmissionsControversy pollutionControversy industrialAccident	Community	anger antiCompetitiveActs lobbying publicHealthControversy ethicsControversy corruptionControversy regulatoryIssues classActionLawsuit iPControversy legalPenalty litigation crimeControversy	Management	managementControversy
Environmental Innovation	sustainabilityControversy	Human Rights	humanRightsControversy childLabor laborExploitation criticalCountriesControversy	Shareholders	accountingControversy accountingRestatement shareholderRightsControversy creditControversy securitiesControversy taxFraudControversy profitWarning earningsDecline insiderDealingControversy activistInvestorActivity proxyFight
Resource Use	environmentalControversy	Product	productControversy privacyControversy advertisementDeceptive mDControversy		
		Workforce	workplaceSafetyControversy diversityControversy layoffs laborDispute wageControversy benefitsControversy		
Panel C: Media Attention Proxies (Category), range (0, inf)					
Environmental		Social		Governance	
Category	RMA Score	Category	RMA Score	Category	RMA Score
Emissions	emissionsBuzz	Community	communityBuzz	Management	managementBuzz
Environmental Innovation	environmentalInnovationBuzz	Human Rights	humanRightsBuzz	Shareholders	shareholdersBuzz
Resource Use	resourceUseBuzz	Product	productBuzz	CSRStrategy	cSRStrategyBuzz
		Workforce	workforceBuzz		
Panel D: Media Attention Proxies (Total Aggregate), range (0, inf)					
Buzz, Mentions					

A.2 Appendix for Chapter 3

A.2.1 Representative sample

TABLE A.2.2: **Representative Sample.** This table presents the degree to which our sample is representative of the Refinitiv TRBC Economic Sectors in terms of total media attention (*Buzz*) received in News and Social media between 1-Jan-2016 and 31-Dec-2021, and market capitalisation as of 31-Dec-2021.

	News Media	Social Media	Market Cap
Basic Materials	19.03%	34.41%	4.36%
Consumer Cyclical	53.25%	43.24%	58.22%
Consumer Non-cyclical	38.91%	44.37%	37.73%
Energy	33.49%	35.96%	24.16%
Financials	25.55%	30.87%	32.61%
Healthcare	25.37%	14.78%	15.41%
Industrials	25.63%	27.97%	5.37%
Technology	45.22%	23.95%	47.57%
Utilities	45.06%	42.89%	18.65%

A.2.2 Persistence of ESG sentiment variables

In this section the variables for sentiment and media attention for each stock were tested for persistence to ensure their suitability as an instrument in out-of-sample forecasts. An AR(1) model was used and persistence determined if the first lag coefficient was significant at 5%. The test was done for all combinations of the sentiment variables (i.e. *ESG*, *News*, *Social*, *E*, *S*, and *G*).

TABLE A.2.3: **Persistence of sentiment variables.** This table reports the proportion of stocks where the sentiment variables (*LnBuzz*, *Sent*, and *RVSent*) exhibit persistence. Persistence is determined where the coefficient of an AR(1) model is significant at 5%.

	ESG	News	Social	E	S	G
lnBuzz	1.00	1.00	1.00	1.00	1.00	1.00
sent	1.00	1.00	0.98	0.91	1.00	0.98
rvSent	0.91	0.98	0.84	0.93	0.93	0.96

A.2.3 In sample results - Individual stocks

TABLE A.2.4: **Joint significance of the sentiment variables for individual stocks.** This table reports the values of the F-statistic for joint significance of the sentiment and attention variables for the 45 stocks in our sample. Columns (1) to (6) present the F-statistic for the ESG-HAR models. The F-statistic is computed when the ESG-HAR model (unrestricted) is estimated by ordinary least squared and compared against the baseline model (restricted). Column (7) presents the average F-statistic across the ESG-HAR models computed using Fishers Combined Probability measure: $\chi^2 = -2 \sum_{i=1}^{n=6} \ln(p_i)$, where p_i is the p-value of the F-test. ***, **, * indicates significance at the 1%, 5% and 10% levels respectively.

	ESG_{NS} (1)	ESG_N (2)	ESG_S (3)	E_{NS} (4)	S_{NS} (5)	G_{NS} (6)	Av (7)
TSLA.O	14.38***	3.23**	23.1***	12.31***	13.8***	14.58***	221.59
AMRS.O	20.0***	1.08	20.24***	6.01***	17.84***	5.91***	192.77
NVAX.O	19.31***	0.92	22.12***	2.0	18.15***	5.91***	185.66
PLUG.O	15.07***	3.87***	17.06***	6.13***	14.91***	8.03***	175.02
MSFT.O	11.78***	8.16***	12.71***	4.97***	8.59***	11.7***	154.5
GE	9.87***	5.29***	17.48***	6.31***	9.1***	7.09***	146.65
BA	10.1***	6.95***	14.19***	6.5***	8.77***	5.79***	138.51
TWTR.N	13.45***	6.55***	10.25***	2.54*	11.03***	3.69**	125.31
RAD	12.93***	3.36**	8.84***	1.94	12.74***	6.97***	123.37
AAPL.O	6.99***	5.27***	14.14***	7.01***	8.84***	3.65**	120.43
GILD.O	9.12***	5.1***	14.45***	3.01**	8.07***	4.39***	115.68
F	10.13***	6.17***	8.88***	3.99***	10.42***	4.1***	114.15
WFC	8.16***	5.82***	4.86***	3.62**	7.9***	10.24***	105.38
JNJ	9.87***	7.54***	4.43***	2.29*	9.08***	6.17***	102.14
CLF	8.87***	0.5	13.28***	2.44*	6.81***	2.75**	89.88
FB.O	5.94***	6.03***	7.52***	1.57	5.76***	5.35***	81.82
WMT	5.24***	3.76**	7.15***	2.8**	6.58***	6.44***	81.05
JPM	6.68***	5.51***	2.86**	3.12**	7.86***	4.79***	77.87
FCEL.O	7.63***	0.68	7.22***	5.9***	3.56**	5.36***	77.17
NFLX.O	6.56***	3.21**	9.11***	1.26	6.45***	3.51**	76.3
XOM	9.18***	5.53***	3.16**	6.52***	2.28*	2.48*	73.47
PCG	7.55***	6.89***	2.07	1.39	4.2***	5.42***	69.06
GS	5.69***	5.13***	1.97	5.02***	6.07***	3.3**	67.76
CVX	9.49***	3.07**	1.83	5.97***	2.58*	2.71**	63.9
MCD	5.27***	3.63**	4.51***	2.43*	6.84***	1.86	60.51
MMM	4.99***	5.94***	1.97	1.96	5.82***	3.53**	59.65
GM	4.08***	2.23*	4.07***	3.23**	5.78***	4.77***	59.29
GEVO.O	4.41***	2.66**	3.96***	4.16***	2.6*	5.34***	56.4
BAC	5.1***	0.18	8.13***	0.3	4.63***	4.05***	56.26
PG	5.13***	2.95**	3.13**	0.74	7.66***	2.68**	54.72
PFE	5.1***	2.66**	5.82***	0.79	5.15***	0.91	49.86
AA	2.8**	3.02**	4.57***	0.8	4.28***	4.44***	47.91
KO	3.75**	5.02***	1.53	0.54	4.7***	3.67**	46.33
MOS	3.52**	5.45***	1.15	1.54	2.84**	3.55**	42.84
FDX	3.9***	5.52***	1.47	1.13	3.95***	1.81	42.26
C	2.72**	0.84	6.31***	2.67**	1.91	0.73	35.59
AMZN.O	1.76	1.34	5.59***	0.83	1.2	2.04	28.97
PEP.O	2.88**	1.12	2.19*	1.02	1.47	1.37	21.47
SRNE.O	1.13	2.8**	2.09*	0.94	0.69	1.14	18.4
X	1.89	0.99	0.4	0.29	2.55*	1.68	16.27
UAL.O	1.0	2.03	2.3*	0.39	0.88	0.77	14.94
DUK	0.97	0.81	0.57	0.75	1.54	2.16*	13.45
D	1.19	1.23	0.75	1.16	0.24	2.04	13.07
NEP	1.56	0.31	0.61	0.81	1.24	0.74	9.78
XEL.O	0.66	0.82	2.14*	0.52	0.15	0.47	8.95

A.2.4 Out of sample results - Individual stocks

TABLE A.2.5: **Out of sample forecasts - MSPE.** This table presents the mean square prediction error (MSPE) of the 1-day ahead forecasts based on a rolling 12month window over the time period 01-Jan-2016 to 31-12-2021. The first column report the MSPE of the baseline HAR model, whilst the remaining columns report the MSPE of the Sentiment HAR models with Clark-West adjustment. The stars indicate significance of the Clark-West test for better predictive ability of the sentiment HAR models over the baseline HAR. ***, **, * indicates significance at the 1%, 5% and 10% levels respectively.

	Baseline (1)	ESG_{NS} (2)	ESG_N (3)	ESG_S (4)	E_{NS} (5)	S_{NS} (6)	G_{NS} (7)
AA	0.523	0.516**	0.517	0.511**	0.518*	0.516**	0.504***
AAPL.O	0.445	0.439**	0.440	0.432***	0.434***	0.434**	0.445
AMRS.O	0.504	0.441***	0.481**	0.440***	0.462***	0.445***	0.468***
AMZN.O	0.411	0.410	0.410	0.402***	0.414	0.410	0.412
BA	0.460	0.454*	0.457	0.445***	0.454*	0.457	0.460
BAC	0.466	0.461	0.464	0.457**	0.465	0.462	0.454***
C	0.452	0.454	0.453	0.449	0.446**	0.453	0.454
CLF	0.560	0.549**	0.560	0.539***	0.552*	0.550**	0.558
CVX	0.394	0.386**	0.390*	0.398	0.383***	0.394	0.395
D	0.418	0.416	0.413	0.420	0.416	0.419	0.408***
DUK	0.410	0.405*	0.406	0.412	0.407	0.411	0.409
F	0.459	0.451**	0.456	0.448***	0.458	0.447***	0.448***
FB.O	0.458	0.451*	0.452*	0.440***	0.461	0.450**	0.451*
FCEL.O	0.410	0.394***	0.402**	0.390***	0.402***	0.398***	0.400***
FDX	0.490	0.480***	0.486	0.489	0.482**	0.480***	0.482**
GE	0.427	0.414***	0.420**	0.398***	0.405***	0.414***	0.410***
GEVO.O	0.553	0.548	0.548	0.549	0.545*	0.552	0.546**
GILD.O	0.497	0.479***	0.495	0.469***	0.483***	0.481***	0.486***
GM	0.474	0.473	0.475	0.476	0.472	0.465**	0.470
GS	0.451	0.446	0.444**	0.447	0.440***	0.446	0.449
JNJ	0.429	0.411***	0.416***	0.421**	0.421**	0.412***	0.418***
JPM	0.455	0.452	0.449**	0.454	0.453	0.451	0.448**
KO	0.431	0.427	0.428	0.428	0.435	0.427	0.426
MCD	0.437	0.428**	0.427***	0.437	0.439	0.427**	0.434
MMM	0.396	0.392*	0.386***	0.393	0.395	0.390**	0.390**
MOS	0.541	0.532**	0.535**	0.533**	0.530**	0.537	0.535
MSFT.O	0.400	0.384***	0.390***	0.381***	0.396	0.393***	0.389***
NEP	0.516	0.503***	0.501***	0.518	0.506**	0.501***	0.514
NFLX.O	0.447	0.440**	0.444	0.432***	0.445	0.439**	0.443
NVAX.O	0.577	0.547***	0.573	0.545***	0.563***	0.546***	0.560***
PCG	0.417	0.403***	0.406***	0.410**	0.417	0.410**	0.403***
PEP.O	0.221	0.220	0.219	0.218	0.220	0.219	0.218
PFE	0.424	0.422	0.425	0.420*	0.424	0.425	0.424
PG	0.420	0.411**	0.413**	0.417	0.417	0.406***	0.414*
PLUG.O	0.570	0.538***	0.560*	0.531***	0.550***	0.537***	0.546***
RAD	0.522	0.496***	0.496***	0.500***	0.512**	0.493***	0.498***
SRNE.O	0.453	0.455	0.458	0.454	0.447	0.454	0.452
TSLA.O	0.528	0.494***	0.519**	0.477***	0.498***	0.501***	0.496***
TWTR.N	0.481	0.471**	0.477*	0.466***	0.472**	0.469***	0.478
UAL.O	0.160	0.160	0.158	0.156***	0.161	0.159	0.159
WFC	0.457	0.446***	0.447***	0.452*	0.453	0.448**	0.441***
WMT	0.452	0.441***	0.446*	0.445**	0.453	0.441***	0.440***
X	0.530	0.519**	0.523	0.526	0.524*	0.521*	0.518**
XEL.O	0.237	0.237	0.236	0.239	0.237	0.239	0.232**
XOM	0.384	0.373***	0.378**	0.383	0.379**	0.384	0.381

TABLE A.2.6: **Out of sample R^2** . This table presents the out of sample R^2 comparing predicted value of $LogRV$ with insample historical returns on 1-day ahead forecasts based on a 12-month rolling window over the time period 01-Jan-2016 to 31-12-2021. The out of sample R^2 is presented per Campbell and Thompson, 2008, i.e. $R_{oos}^2 = 1 - (\sum(y - \hat{y})^2 / \sum(y - \bar{y})^2)$. Column 1 presents the OOS R^2 reported in percent for the baseline-HAR and can be interpreted as the increase (decrease) in forecasting accuracy over the historical average return. Columns 2 to 7 present the percent increase (decrease) of the OOS R^2 of the Sentiment-HAR model over the OOS R^2 of the baseline-HAR.

	Baseline (1)	ESG_{NS} (2)	ESG_N (3)	ESG_S (4)	E_{NS} (5)	S_{NS} (6)	G_{NS} (7)
AA	36.72	36.45	35.98	36.29	36.14	36.37	37.08
AAPL.O	55.15	54.97	54.79	55.37	55.25	55.20	54.73
AMRS.O	46.45	49.16	46.22	49.28	48.03	48.84	47.64
AMZN.O	57.65	57.12	57.11	57.47	56.97	56.97	57.02
BA	55.87	55.34	55.28	56.06	55.56	55.27	55.07
BAC	51.13	50.62	50.81	50.91	50.26	50.78	51.38
C	54.14	53.38	53.54	53.66	54.00	53.50	53.49
CLF	41.98	41.78	41.36	42.44	41.53	41.81	41.24
CVX	61.02	60.70	60.76	60.24	61.32	60.47	60.22
D	57.98	57.57	57.57	57.25	57.40	57.38	57.95
DUK	59.57	59.15	59.06	59.03	59.18	59.07	59.08
F	51.41	51.22	50.91	51.29	51.01	51.39	51.53
FB.O	53.13	52.78	52.71	53.44	52.29	52.77	52.72
FCEL.O	61.70	61.91	61.42	62.15	61.67	61.76	61.65
FDX	48.18	48.16	47.65	47.61	47.85	48.18	47.81
GE	61.20	61.19	61.13	61.80	61.69	61.22	61.57
GEVO.O	43.44	42.67	42.75	42.53	42.65	42.28	42.99
GILD.O	46.75	47.37	46.23	47.91	46.84	47.14	47.05
GM	49.16	48.56	48.48	48.21	48.68	48.97	48.71
GS	51.08	50.73	51.00	50.72	50.92	50.70	50.57
JNJ	50.97	51.24	50.90	50.91	50.76	51.25	51.06
JPM	52.68	52.47	52.64	52.11	52.20	52.42	52.40
KO	55.64	55.40	55.32	55.40	54.82	55.34	55.19
MCD	54.03	53.89	54.03	53.33	53.17	53.83	53.67
MMM	57.81	57.53	58.14	57.38	57.46	57.66	57.69
MOS	43.23	43.07	43.00	42.92	43.02	42.80	42.74
MSFT.O	61.05	61.52	61.28	61.54	60.70	61.00	61.31
NEP	44.52	44.42	44.28	43.60	44.28	44.54	44.08
NFLX.O	56.31	56.10	55.95	56.51	55.81	56.09	56.03
NVAX.O	33.99	34.30	33.30	34.05	33.87	34.27	33.84
PCG	60.27	60.19	60.14	59.79	59.51	59.93	59.87
PEP.O	74.65	74.44	74.59	74.52	74.44	74.48	74.51
PFE	54.85	54.42	54.39	54.56	54.52	54.23	54.41
PG	54.30	53.84	54.03	53.76	53.96	54.32	54.06
PLUG.O	39.28	39.79	38.36	40.32	39.28	39.92	39.72
RAD	46.72	47.41	47.44	47.19	46.42	47.66	47.29
SRNE.O	59.27	58.66	58.24	58.64	58.44	58.72	58.80
TSLA.O	48.48	49.63	48.48	50.39	49.34	49.30	49.49
TWTR.N	50.70	50.39	50.39	50.84	50.77	50.55	50.28
UAL.O	81.77	81.58	81.70	81.89	81.50	81.66	81.74
WFC	52.42	52.44	52.58	51.91	51.87	52.30	52.58
WMT	51.44	51.48	51.22	51.14	50.64	51.52	51.40
X	45.37	45.12	44.67	44.96	45.09	44.92	45.26
XEL.O	72.31	71.95	72.00	71.93	72.06	71.83	72.47
XOM	61.64	61.69	61.38	61.19	61.36	61.09	61.20

A.3 Appendix for Chapter 4

A.3.1 MSCI ESG key issues

TABLE A.3.7: **MSCI key issues to pillar scores.** This table outlines the 37 key issues identified by MSCI as being financially relevant to ESG performance measures, grouped into their respective pillars. Accessed at <https://www.msci.com/zh/esg-ratings> on 7 January 2025

Pillar Group	Category	Issue
Environmental	Climate change	Carbon emissions Product carbon footprint Financing environmental impact Climate change vulnerability
	Natural resources	Water stress Biodiversity and land use
	Pollution and waste	Raw material sourcing Toxic emissions and waste Packaging material and waste Electronic waste
	Environmental opportunities	Opportunities in clean tech Opportunities in green building Opportunities in renewable energy
Social	Human capital	Labour management Human capital development Health and safety Supply chain labour standards
	Product liability	Product quality and safety Chemical safety Financial product safety Privacy and data security Responsible investment
	Stakeholder opposition Social opportunities	Health and demographic risk Controversial sourcing Access to communications Access to finance Access to healthcare Opportunities in health and nutrition
Governance	Corporate governance	Board diversity Executive pay Ownership and control Accounting
	Corporate behaviour	Business ethics Anti-competitive practices Tax transparency Corruption and instability Financial system stability

A.3.2 Aggregating RMEA category scores to pillar scores

A benefit in using the Refinitiv Marketpsych ESG Analytics database is the granularity with which data is available with key features being the available of sentiment at the topic level (e.g. *sustainableInnovation* or *privacyEfforts*), sentiment and media attention variables at the category level (e.g. *emissions*, *management*, or *product*). In this section we outline the procedure to aggregate the category sentiment variables (*ESG*, *Controversy*), and media attention variable (*Buzz*) cross-sectionally to an environmental, social, or governance pillar *Sent* and *Buzz* scores. Table A.3.8 summarises the individual categories belonging to each pillar group.

TABLE A.3.8: **RMEA Category to Pillar scores.** Grouping of category scores to their pillar groups.

Pillar Group	Category
Environmental	emissions
	environmentalInnovation
	resourceUse
Social	community
	humanRights
	product
	workforce
Governance	cSRStrategy
	management
	shareholders

We start by combining the *ESG* and *Controversy* scores to form a single measure of sentiment (*Sent*). By its construction, the underlying variables that contribute negatively to the *ESG* score may also contribute to the *Controversy* score, however, the reverse may not be true. Therefore, to capture the overall sentiment of a company at any point in time, it is prudent for us to merge these two variables together. The *Sent* variable is therefore constructed as the simple average of the timestamped observation of the *ESG* and negated *Controversy* for each company j , category c , media type k and timestamp i .¹ As the *Controversy* score is negative in its tonality (i.e. a higher score is subjectively negative), it is negated to align its tonality with the *ESG* measure. For brevity, we suppress the company, category and media type subscripts:

$$Sent_i = \frac{1}{2}(-Controversy_i + ESG_i), \quad (\text{A.1})$$

Next, we aggregate the intraday to daily category scores following the procedure outlined in

¹This approach is different to literature that combines the ESG and Controversy scores of a related product, Thompson Reuters Asset 4 (see Yang et al., 2024, as an example). This is primarily due to differences in how the *Controversy* scores are formulated between the two products.

Refinitiv Marketpsych ESG Analytics whitepaper Refinitiv (2020). The aggregation window is selected between 09:35 on day t to 09:25 on day $t-1$ to include overnight and pre-market sentiment. We exclude observations in the 5-minutes following and preceding market open to exclude any potential noise associated with the opening session. The category $Sent$ measure is computed as the $Buzz$ weighted average of observations. The category $Buzz$ measure is computed as the sum of observations within the aggregation window.

$$Sent_{t,c} = \frac{\sum_i Sent_{i,c} \times Buzz_{i,c}}{\sum_i Buzz_{i,c}}, \quad (\text{A.2})$$

$$Buzz_{t,c} = \sum_i Buzz_{i,c}, \quad (\text{A.3})$$

Next, we combine each of the category variables for $Sent$ and $Buzz$ cross-sectionally to form the individual E , S , and G pillar scores. The $Sent$ scores are calculated as the $Buzz$ -weighted average of the category scores belonging to the pillar group. By using a $Buzz$ -weighted average, we allow the data to determine each category's relevance to the overall pillar (or composite score), based on the level of attention it receives. This approach enables dynamic adjustment of materiality, rather than relying on fixed weights. The $Buzz$ scores on the other hand are calculated as the total sum of category $Buzz$ in each respective pillar and composite ESG groups.

$$Buzz_{P,i} = \sum_{c \in P} Buzz_{c \in P,i}, \quad (\text{A.4})$$

$$Sent_{P,i} = \sum_{c \in P} \omega_{c \in P,i} \times Sent_{c \in P,i}, \quad (\text{A.5})$$

$$\omega_{c \in P,i} = \frac{Buzz_{c,i}}{\sum_{c \in P} Buzz_i}, \quad (\text{A.6})$$

where $c \in P$ represents the category variable c belonging to pillar group P , P represents the E , S , and G pillar groups, and ω represents the category $Buzz$ -weight.

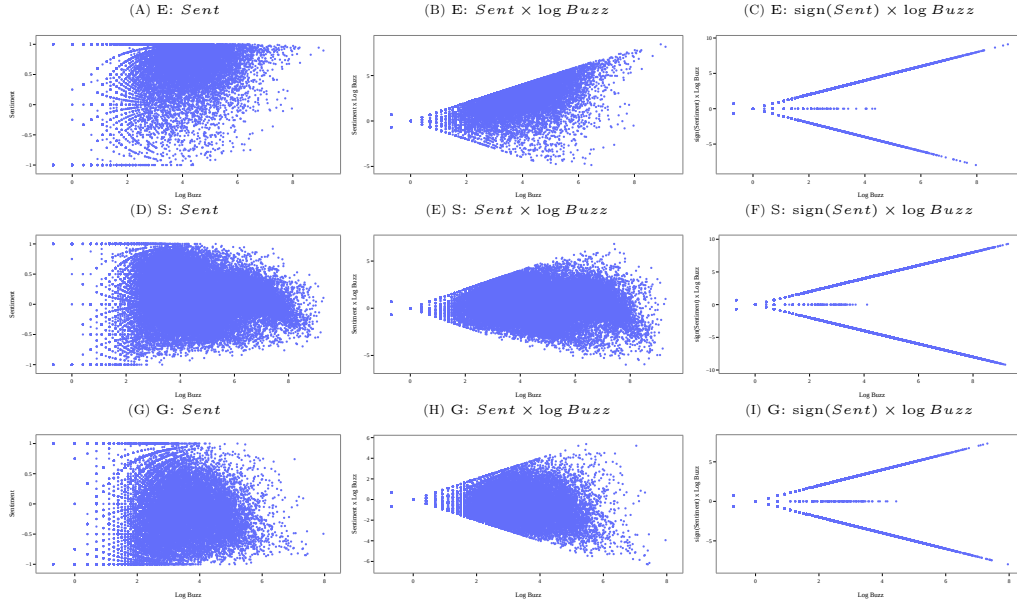
A.3.3 Relation between sentiment and media attention

When formulating the greenness score using sentiment variables as a proxy for ESG performance, we make an important decision to scale the *Buzz* materiality weight, ω , by the sign of sentiment instead of the sentiment value. To understand the reasoning behind this decision, we plot the relationship between the logarithm of media attention and three iterations of sentiment: *Sent* (left panel); $Sent \times Buzz$ (middle vertical panel); and $\text{sign}(Sent) \times \log Buzz$ (right panel) in Figure A.3.1. We do this for the environmental pillar (top panel), social media (middle horizontal panel), and governance (bottom panel).

The left panel describes the relationship between $\log Buzz$ and *Sent*. We detect a positive bias in the sentiment variable relating to the environmental pillar where $\log Buzz$ gets large, the positive observations of *Sent* outweigh negative. The number of extreme positive observations also appears to be greater than those around zero. For the governance pillar, the opposite dynamic appears to take place, although the number of extreme negative observations becomes less as $\log Buzz$ gets larger. The social pillar offers the most balanced however we observe that as $\log Buzz$ gets larger, sentiment becomes more neutral with observations hovering at or around zero. The tendency of *Sent* to become more neutral as *Buzz* gets larger is not surprising. With lower levels of media attention extreme feelings stand out whilst a greater attention leads to a larger pool of diverse opinions. These diverse opinions will have the effect of leading to a consensus view which may be a strong positive or negative signal if the majority have the same opinion. However more often than not, the views will cancel each other out leading to a *Sent* measure that neutral.

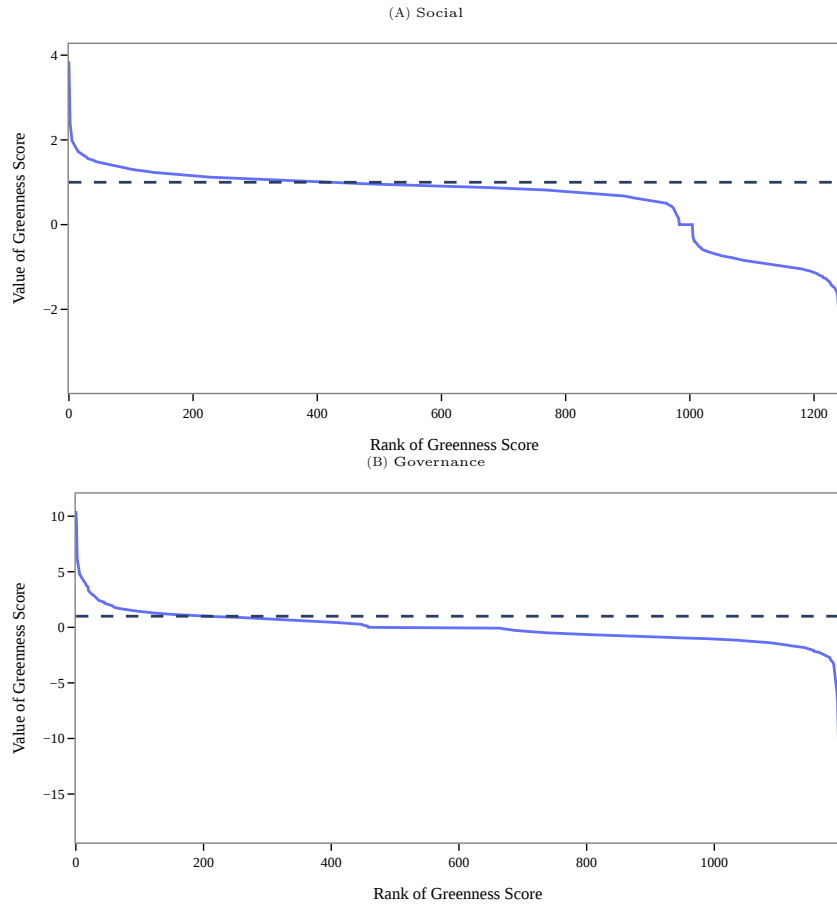
We see this interaction by plotting *Buzz* against the interaction of *Sent* and *Buzz* variables (middle vertical panel). Especially for the social pillar we see observations with a value at or around zero as *Buzz* gets larger. If we were to go with this signal, we would see a greenness score that is close to zero, despite whether the value for media attention signalled its materiality. Therefore, by taking the sign, we are able to maintain the trend of sentiment on that day, whether collectively it was positive or negative, without losing meaning in the materiality score.

FIGURE A.3.1: **Sentiment vs Buzz**. This figure plots $\log Buzz$ (x-axis) against $Sent$ (left panel), $Sent \times \log Buzz$ (middle vertical panel), and $\text{sign}(Sent) \log Buzz$ (right panel) along the y-axis for the environmental (top panel), social (middle horizontal panel), and governance (bottom panel) pillars. For the purposes of illustration, a random sample of 30 companies were selected to display daily values between 01-Jan-2016 and 31-Dec-2021. In total this figure plots 31,409 paired observations



A.3.4 Breaking Buzz!

FIGURE A.3.2: **Breaking Buzz!**. The figure plots Breaking Buzz! for the Social (Panel (A)) and Governance (Panel (B)) pillars as at 31 December 2021. Materiality weights are ranked from highest to lowest and presented in descending order



A.3.5 Robustness checks

A.3.5.1 Regression results of the value-weighted GMB-PST factor

The regression results of the value-weighted GMB-PST factor are presented here. Tables A.3.9 to A.3.11 presents the results of the value-weighted GMB-PST factor for the environmental, social, and governance pillars respectively.

TABLE A.3.9: **Value-weighted GMB-PST - Environment.** Monthly time-series regressions are estimated using data from January 2016 to December 2021. GMB-PST is the GMB factor computed using Pástor et al., 2022 methodology from MSCI data. Mkt-Rf is the excess market return. SMB and HML are the size and value factors of Fama and French, 1993. MOM is the momentum factor of Carhart, 1997. LIQ is the traded liquidity factor of Pástor and Stambaugh, 2003. RMW and CMA are the profitability and investment factors of Fama and French, 2015. ME, I/A, and ROE are the size, investment, and profitability factors of Hou et al., 2015. EG is the expected growth factor of Hou et al., 2021. Returns are in percent per month. Robust t-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
const	0.58 (2.02)	0.69 (2.12)	0.45 (1.76)	0.45 (1.74)	0.46 (1.78)	0.49 (2.01)	0.53 (1.82)	0.33 (1.15)
Mkt-RF		-0.08 (-0.90)	0.03 (0.57)	0.04 (0.56)	0.03 (0.41)	0.07 (1.12)	-0.00 (-0.05)	0.06 (0.90)
SMB			-0.29 (-2.69)	-0.28 (-2.48)	-0.30 (-2.62)	-0.39 (-3.20)		
HML			-0.24 (-3.37)	-0.24 (-3.01)	-0.23 (-3.15)	-0.19 (-2.18)		
MOM				0.01 (0.13)				
LIQ					0.03 (0.45)			
RMW						-0.24 (-1.70)		
CMA						-0.02 (-0.11)		
ME							-0.37 (-2.45)	-0.29 (-1.84)
I/A							-0.28 (-2.26)	-0.04 (-0.25)
ROE							0.01 (0.07)	-0.23 (-2.31)
EG								0.43 (2.74)
Observations	69	69	69	69	69	69	69	69
R2	0.00	0.02	0.36	0.36	0.36	0.39	0.31	0.39

TABLE A.3.10: **Value-weighted GMB-PST - Social.** Monthly time-series regressions are estimated using data from January 2016 to December 2021. GMB-PST is the GMB factor computed using Pástor et al., 2022 methodology from MSCI data. Mkt-Rf is the excess market return. SMB and HML are the size and value factors of Fama and French, 1993. MOM is the momentum factor of Carhart, 1997. LIQ is the traded liquidity factor of Pástor and Stambaugh, 2003. RMW and CMA are the profitability and investment factors of Fama and French, 2015. ME, I/A, and ROE are the size, investment, and profitability factors of Hou et al., 2015. EG is the expected growth factor of Hou et al., 2021. Returns are in percent per month. Robust t-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
const	-0.10 (-0.45)	0.06 (0.25)	0.02 (0.08)	0.01 (0.06)	0.03 (0.14)	0.03 (0.17)	-0.02 (-0.08)	-0.04 (-0.19)
Mkt-RF		-0.11 (-1.76)	-0.09 (-1.49)	-0.09 (-1.23)	-0.11 (-1.64)	-0.18 (-2.61)	-0.13 (-2.39)	-0.12 (-2.12)
SMB			-0.04 (-0.41)	-0.03 (-0.34)	-0.07 (-0.67)	0.07 (0.70)		
HML			-0.04 (-0.57)	-0.03 (-0.36)	-0.02 (-0.30)	0.01 (0.12)		
MOM				0.03 (0.27)				
LIQ					0.06 (0.84)			
RMW						0.24 (1.63)		
CMA						-0.35 (-2.85)		
ME							0.10 (1.02)	0.11 (1.06)
I/A							-0.26 (-2.87)	-0.23 (-1.91)
ROE							0.15 (1.60)	0.12 (0.89)
EG								0.05 (0.38)
Observations	69	69	69	69	69	69	69	69
R2	0.00	0.07	0.08	0.09	0.09	0.22	0.21	0.21

TABLE A.3.11: **Value-weighted GMB-PST - Governance.** Monthly time-series regressions are estimated using data from January 2016 to December 2021. GMB-PST is the GMB factor computed using Pástor et al., 2022 methodology from MSCI data. Mkt-Rf is the excess market return. SMB and HML are the size and value factors of Fama and French, 1993. MOM is the momentum factor of Carhart, 1997. LIQ is the traded liquidity factor of Pástor and Stambaugh, 2003. RMW and CMA are the profitability and investment factors of Fama and French, 2015. ME, I/A, and ROE are the size, investment, and profitability factors of Hou et al., 2015. EG is the expected growth factor of Hou et al., 2021. Returns are in percent per month. Robust t-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
const	0.08 (0.41)	0.27 (1.49)	0.29 (1.39)	0.27 (1.38)	0.26 (1.42)	0.22 (1.15)	0.23 (1.18)	0.33 (1.64)
Mkt-RF		-0.13 (-3.33)	-0.13 (-2.53)	-0.11 (-2.62)	-0.10 (-2.19)	-0.13 (-2.73)	-0.09 (-1.94)	-0.12 (-2.49)
SMB			-0.04 (-0.37)	-0.02 (-0.15)	0.00 (0.01)	0.03 (0.34)		
HML			0.05 (0.80)	0.08 (1.30)	0.01 (0.23)	-0.05 (-0.81)		
MOM				0.09 (0.98)				
LIQ					-0.10 (-1.07)			
RMW						0.17 (1.30)		
CMA						0.22 (1.27)		
ME							0.02 (0.18)	-0.02 (-0.19)
I/A							0.20 (1.88)	0.07 (0.75)
ROE							0.13 (1.90)	0.25 (3.00)
EG								-0.22 (-2.76)
Observations	69	69	69	69	69	69	69	69
R2	0.00	0.13	0.14	0.16	0.17	0.22	0.24	0.29

A.3.5.2 Varying K-parameter in Breaking Buzz!

TABLE A.3.12: **Value-weighted GMB performance (Environment, k=6)**. We estimate monthly time-series regressions using data from January 2016 to December 2021. The dependent variable is the GMB factor computed as the difference between the value-weighted returns on the green portfolio and brown portfolios formed by the top (bottom) third of stocks ranked by their greenness score in the previous month ($g_{j,t-1}$). The GMB factor is constructed with long run history of 6 months (weighting parameter k=6 in Eqn 4.1). Mkt-Rf is the excess market return. SMB and HML are the size and value factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997). LIQ is the traded liquidity factor of Pástor and Stambaugh (2003). RMW and CMA are the profitability and investment factors of Fama and French (2015). ME, I/A, and ROE are the size, investment, and profitability factors of Hou et al. (2015). EG is the expected growth factor of Hou et al. (2021). Returns are in percent per month. Robust t-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
const	0.07 (0.39)	0.14 (0.77)	0.07 (0.37)	0.04 (0.25)	0.07 (0.36)	0.11 (0.58)	0.08 (0.39)	0.02 (0.10)
Mkt-RF		-0.05 (-1.23)	-0.01 (-0.13)	0.03 (0.67)	-0.00 (-0.01)	0.02 (0.45)	-0.01 (-0.18)	0.01 (0.16)
SMB			-0.15 (-1.55)	-0.10 (-1.10)	-0.14 (-1.18)	-0.22 (-2.47)		
HML			-0.02 (-0.38)	0.04 (0.82)	-0.03 (-0.45)	0.01 (0.18)		
MOM				0.16 (1.79)				
LIQ					-0.02 (-0.28)			
RMW						-0.16 (-1.63)		
CMA						0.02 (0.10)		
ME							-0.11 (-1.00)	-0.09 (-0.80)
I/A							0.00 (0.04)	0.07 (0.46)
ROE							0.03 (0.59)	-0.02 (-0.29)
EG								0.11 (0.84)
Observations	66	66	66	66	66	66	66	66
R2	0.00	0.02	0.12	0.22	0.12	0.15	0.08	0.09

TABLE A.3.13: **Value-weighted GMB performance (Environment, k=12)**. We estimate monthly time-series regressions using data from January 2016 to December 2021. The dependent variable is the GMB factor computed as the difference between the value-weighted returns on the green portfolio and brown portfolios formed by the top (bottom) third of stocks ranked by their greenness score in the previous month ($g_{j,t-1}$). The GMB factor is constructed with long run history of 12 months (weighting parameter $k=12$ in Eqn 4.1). Mkt-Rf is the excess market return. SMB and HML are the size and value factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997). LIQ is the traded liquidity factor of Pástor and Stambaugh (2003). RMW and CMA are the profitability and investment factors of Fama and French (2015). ME, I/A, and ROE are the size, investment, and profitability factors of Hou et al. (2015). EG is the expected growth factor of Hou et al. (2021). Returns are in percent per month. Robust t-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
const	0.08 (0.41)	0.13 (0.63)	0.05 (0.21)	0.02 (0.08)	0.05 (0.22)	0.07 (0.32)	0.02 (0.10)	-0.02 (-0.09)
Mkt-RF		-0.04 (-0.84)	0.00 (0.04)	0.05 (1.04)	0.00 (0.04)	0.04 (0.85)	0.01 (0.29)	0.03 (0.62)
SMB			-0.17 (-1.72)	-0.12 (-1.29)	-0.17 (-1.38)	-0.24 (-2.59)		
HML			0.00 (0.02)	0.09 (1.28)	0.00 (0.02)	-0.00 (-0.02)		
MOM				0.20 (2.67)				
LIQ					0.00 (0.02)			
RMW						-0.14 (-1.72)		
CMA						0.13 (0.66)		
ME							-0.09 (-0.75)	-0.07 (-0.55)
I/A							0.04 (0.41)	0.10 (0.67)
ROE							0.10 (1.36)	0.04 (0.44)
EG								0.11 (0.67)
Observations	60	60	60	60	60	60	60	60
R2	0.00	0.01	0.11	0.27	0.11	0.15	0.10	0.11

TABLE A.3.14: **Value-weighted GMB performance (Social, k=6)**. We estimate monthly time-series regressions using data from January 2016 to December 2021. The dependent variable is the GMB factor computed as the difference between the value-weighted returns on the green portfolio and brown portfolios formed by the top (bottom) third of stocks ranked by their greenness score in the previous month ($g_{j,t-1}$). The GMB factor is constructed with long run history of 6 months (weighting parameter $k=6$ in Eqn 4.1). Mkt-Rf is the excess market return. SMB and HML are the size and value factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997). LIQ is the traded liquidity factor of Pástor and Stambaugh (2003). RMW and CMA are the profitability and investment factors of Fama and French (2015). ME, I/A, and ROE are the size, investment, and profitability factors of Hou et al. (2015). EG is the expected growth factor of Hou et al. (2021). Returns are in percent per month. Robust t-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
const	-0.45 (-1.58)	-0.23 (-0.88)	-0.17 (-0.61)	-0.15 (-0.52)	-0.18 (-0.63)	-0.12 (-0.42)	-0.14 (-0.49)	-0.07 (-0.24)
Mkt-RF		-0.15 (-2.04)	-0.17 (-2.09)	-0.20 (-2.38)	-0.16 (-2.15)	-0.16 (-2.01)	-0.16 (-1.90)	-0.18 (-2.03)
SMB			-0.00 (-0.04)	-0.04 (-0.37)	0.01 (0.07)	-0.07 (-0.54)		
HML			0.10 (1.20)	0.05 (0.53)	0.09 (1.03)	0.17 (1.55)		
MOM				-0.13 (-1.33)				
LIQ					-0.03 (-0.32)			
RMW						-0.14 (-0.76)		
CMA						-0.13 (-0.60)		
ME							-0.08 (-0.57)	-0.10 (-0.70)
I/A							0.09 (0.53)	0.02 (0.07)
ROE							-0.17 (-1.87)	-0.10 (-0.80)
EG								-0.13 (-0.62)
Observations	66	66	66	66	66	66	66	66
R2	0.00	0.09	0.11	0.14	0.11	0.13	0.13	0.13

TABLE A.3.15: **Value-weighted GMB performance (Social, k=12)**. We estimate monthly time-series regressions using data from January 2016 to December 2021. The dependent variable is the GMB factor computed as the difference between the value-weighted returns on the green portfolio and brown portfolios formed by the top (bottom) third of stocks ranked by their greenness score in the previous month ($g_{j,t-1}$). The GMB factor is constructed with long run history of 12 months (weighting parameter $k=12$ in Eqn 4.1). Mkt-Rf is the excess market return. SMB and HML are the size and value factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997). LIQ is the traded liquidity factor of Pástor and Stambaugh (2003). RMW and CMA are the profitability and investment factors of Fama and French (2015). ME, I/A, and ROE are the size, investment, and profitability factors of Hou et al. (2015). EG is the expected growth factor of Hou et al. (2021). Returns are in percent per month. Robust t-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
const	-0.33 (-1.05)	-0.10 (-0.35)	0.07 (0.23)	0.08 (0.27)	0.06 (0.19)	0.17 (0.53)	0.01 (0.03)	0.07 (0.21)
Mkt-RF		-0.16 (-1.93)	-0.19 (-2.27)	-0.21 (-2.38)	-0.18 (-2.31)	-0.17 (-2.23)	-0.18 (-2.02)	-0.20 (-2.30)
SMB			0.02 (0.17)	-0.00 (-0.03)	0.04 (0.31)	-0.09 (-0.71)		
HML			0.17 (1.88)	0.14 (1.39)	0.16 (1.60)	0.27 (2.10)		
MOM				-0.07 (-0.86)				
LIQ					-0.04 (-0.46)			
RMW						-0.23 (-1.13)		
CMA						-0.13 (-0.71)		
ME							0.02 (0.16)	-0.01 (-0.07)
I/A							0.12 (0.80)	0.04 (0.17)
ROE							-0.11 (-1.23)	-0.04 (-0.27)
EG								-0.14 (-0.64)
Observations	60	60	60	60	60	60	60	60
R2	0.00	0.09	0.16	0.17	0.17	0.20	0.13	0.14

TABLE A.3.16: **Value-weighted GMB performance (Governance, k=6)**. We estimate monthly time-series regressions using data from January 2016 to December 2021. The dependent variable is the GMB factor computed as the difference between the value-weighted returns on the green portfolio and brown portfolios formed by the top (bottom) third of stocks ranked by their greenness score in the previous month ($g_{j,t-1}$). The GMB factor is constructed with long run history of 6 months (weighting parameter $k=6$ in Eqn 4.1). Mkt-Rf is the excess market return. SMB and HML are the size and value factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997). LIQ is the traded liquidity factor of Pástor and Stambaugh (2003). RMW and CMA are the profitability and investment factors of Fama and French (2015). ME, I/A, and ROE are the size, investment, and profitability factors of Hou et al. (2015). EG is the expected growth factor of Hou et al. (2021). Returns are in percent per month. Robust t-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
const	-0.45 (-1.99)	-0.25 (-1.11)	-0.24 (-1.06)	-0.20 (-0.92)	-0.24 (-1.09)	-0.21 (-0.97)	-0.27 (-1.21)	-0.25 (-0.98)
Mkt-RF		-0.14 (-3.07)	-0.12 (-2.08)	-0.17 (-2.97)	-0.12 (-2.23)	-0.13 (-2.11)	-0.10 (-1.78)	-0.11 (-1.78)
SMB			-0.12 (-1.12)	-0.18 (-1.75)	-0.12 (-0.88)	-0.14 (-1.33)		
HML			0.08 (1.45)	0.01 (0.12)	0.08 (1.21)	0.13 (1.43)		
MOM				-0.19 (-2.41)				
LIQ					-0.01 (-0.11)			
RMW						-0.04 (-0.25)		
CMA						-0.13 (-0.69)		
ME							-0.14 (-1.18)	-0.15 (-1.22)
I/A							0.08 (0.71)	0.06 (0.42)
ROE							-0.03 (-0.27)	-0.00 (-0.04)
EG								-0.04 (-0.29)
Observations	66	66	66	66	66	66	66	66
R2	0.00	0.12	0.16	0.25	0.16	0.17	0.15	0.15

TABLE A.3.17: **Value-weighted GMB performance (Governance, k=12)**. We estimate monthly time-series regressions using data from January 2016 to December 2021. The dependent variable is the GMB factor computed as the difference between the value-weighted returns on the green portfolio and brown portfolios formed by the top (bottom) third of stocks ranked by their greenness score in the previous month ($g_{j,t-1}$). The GMB factor is constructed with long run history of 12 months (weighting parameter $k=12$ in Eqn 4.1). Mkt-Rf is the excess market return. SMB and HML are the size and value factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997). LIQ is the traded liquidity factor of Pástor and Stambaugh (2003). RMW and CMA are the profitability and investment factors of Fama and French (2015). ME, I/A, and ROE are the size, investment, and profitability factors of Hou et al. (2015). EG is the expected growth factor of Hou et al. (2021). Returns are in percent per month. Robust t-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
const	-0.49 (-1.99)	-0.34 (-1.43)	-0.31 (-1.25)	-0.28 (-1.18)	-0.31 (-1.27)	-0.24 (-1.05)	-0.35 (-1.41)	-0.29 (-1.08)
Mkt-RF		-0.10 (-2.29)	-0.09 (-1.47)	-0.13 (-2.31)	-0.09 (-1.69)	-0.11 (-1.72)	-0.08 (-1.30)	-0.10 (-1.59)
SMB			-0.14 (-1.06)	-0.18 (-1.50)	-0.15 (-0.90)	-0.18 (-1.41)		
HML			0.10 (1.64)	0.03 (0.41)	0.11 (1.64)	0.20 (2.17)		
MOM				-0.17 (-1.92)				
LIQ					0.02 (0.19)			
RMW						-0.07 (-0.38)		
CMA						-0.26 (-1.33)		
ME							-0.17 (-1.20)	-0.20 (-1.33)
I/A							0.03 (0.23)	-0.05 (-0.29)
ROE							-0.08 (-0.81)	-0.01 (-0.06)
EG								-0.14 (-0.91)
Observations	60	60	60	60	60	60	60	60
R2	0.00	0.06	0.11	0.18	0.11	0.16	0.10	0.12

A.3.5.3 Equal-weighted GMB factor

The results of the equal-weighted GMB factor are presented here. Figure A.3.3 plots the cumulative returns of the equal-weighted GMB and GMB-PST factors for the environmental, social and governance pillars. For completeness, Table A.3.18 presents common performance statistics for these factors contrasted with the market portfolio. Tables A.3.19 to A.3.21 present the results of the equal-weighted GMB factor for the environmental, social, and governance pillars respectively.

TABLE A.3.18: **Performance Statistics - Equal weighted.** This table presents some common performance statistics of the excess returns of the market portfolio, and the GMB and GMB-PST factors for the environmental (E), social (S), and governance (G) pillars. The S&P500 is used as the proxy for the market portfolio.

	Mkt-RF	GMB			GMB-PST		
		E	S	G	E	S	G
Cum. Ret	147.81%	-18.05%	12.16%	-8.42%	-9.53%	-19.52%	-14.98%
Ann. Ret	19.90%	-3.90%	2.32%	-1.74%	-1.98%	-4.25%	-3.19%
Ann. Std	15.21%	4.92%	8.43%	4.21%	6.15%	6.17%	5.45%
IR	1.12	-0.65	0.27	-0.33	-0.24	-0.55	-0.47

FIGURE A.3.3: **GMB - Equal Weighted.** This figure presents the sustainability factors for Environmental (Panel (A)), Social (Panel (B)), and Governance pillars (Panel (C)). The GMB factor is defined as the returns of the Green portfolio minus the returns of the Brown portfolio between May 2016 and December 2021. The Green (Brown) portfolio are formed of the companies with $g_{i,t}$ scores in the top (bottom) third in a given month-year. The red (grey) line represents the cumulative equal-weighted returns of the GMB factor formed from the RMEA (MSCI) scores.

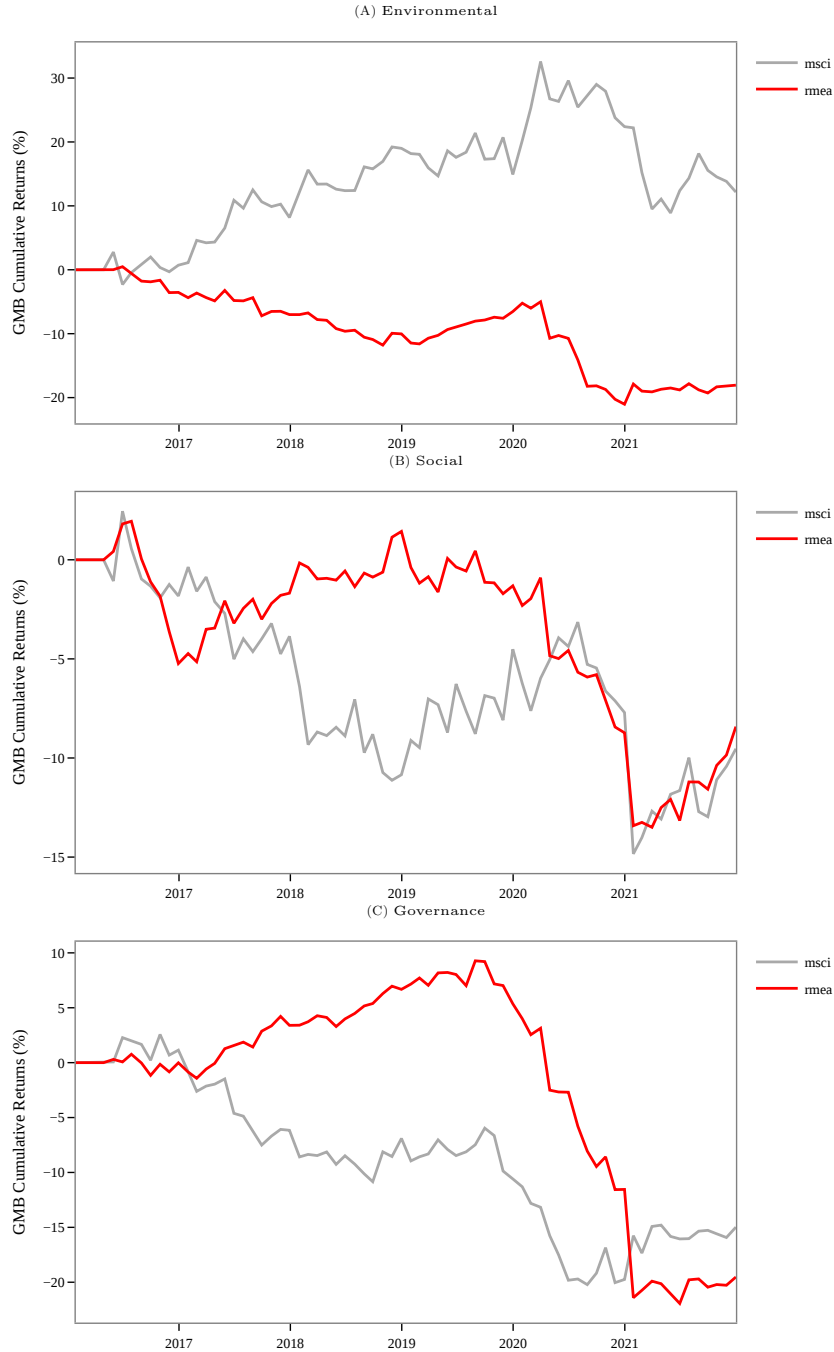


TABLE A.3.19: **Equal-weighted GMB Performance - Environment.** We estimate monthly time-series regressions using data from January 2016 to December 2021. The dependent variable is the GMB factor computed as the difference between the equal-weighted returns on the green portfolio and brown portfolios formed by the top (bottom) third of stocks ranked by their greenness score in the previous month ($g_{j,t-1}$). Mkt-Rf is the excess market return. SMB and HML are the size and value factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997). LIQ is the traded liquidity factor of Pástor and Stambaugh (2003). RMW and CMA are the profitability and investment factors of Fama and French (2015). ME, I/A, and ROE are the size, investment, and profitability factors of Hou et al. (2015). EG is the expected growth factor of Hou et al. (2021). Returns are in percent per month. Robust t-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
const	-0.28 (-1.59)	-0.10 (-0.65)	-0.12 (-0.74)	-0.13 (-0.89)	-0.15 (-1.02)	-0.11 (-0.69)	-0.14 (-0.89)	-0.17 (-0.96)
Mkt-RF		-0.13 (-2.41)	-0.10 (-1.62)	-0.09 (-1.34)	-0.07 (-1.47)	-0.08 (-1.41)	-0.10 (-1.49)	-0.09 (-1.33)
SMB			-0.10 (-1.10)	-0.09 (-0.86)	-0.04 (-0.42)	-0.14 (-1.57)		
HML			0.02 (0.54)	0.05 (0.92)	-0.02 (-0.51)	0.03 (0.49)		
MOM				0.06 (0.71)				
LIQ					-0.13 (-1.80)			
RMW						-0.09 (-0.88)		
CMA						0.03 (0.24)		
ME							-0.05 (-0.52)	-0.04 (-0.40)
I/A							0.04 (0.45)	0.07 (0.75)
ROE							0.06 (1.30)	0.02 (0.35)
EG								0.06 (0.62)
Observations	69	69	69	69	69	69	69	69
R2	0.00	0.15	0.18	0.19	0.25	0.19	0.18	0.18

TABLE A.3.20: **Equal-weighted GMB performance - Social.** We estimate monthly time-series regressions using data from January 2016 to December 2021. The dependent variable is the GMB factor computed as the difference between the equal-weighted returns on the green portfolio and brown portfolios formed by the top (bottom) third of stocks ranked by their greenness score in the previous month ($g_{j,t-1}$). Mkt-Rf is the excess market return. SMB and HML are the size and value factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997). LIQ is the traded liquidity factor of Pástor and Stambaugh (2003). RMW and CMA are the profitability and investment factors of Fama and French (2015). ME, I/A, and ROE are the size, investment, and profitability factors of Hou et al. (2015). EG is the expected growth factor of Hou et al. (2021). Returns are in percent per month. Robust t-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
const	-0.12 (-0.80)	-0.00 (-0.03)	-0.09 (-0.64)	-0.08 (-0.63)	-0.09 (-0.66)	-0.10 (-0.78)	-0.11 (-0.87)	-0.15 (-1.10)
Mkt-RF		-0.08 (-2.41)	-0.03 (-0.64)	-0.03 (-0.77)	-0.03 (-0.84)	-0.07 (-1.63)	-0.03 (-0.73)	-0.02 (-0.38)
SMB			-0.20 (-2.81)	-0.20 (-2.53)	-0.20 (-2.20)	-0.12 (-1.90)		
HML			-0.02 (-0.59)	-0.03 (-0.62)	-0.02 (-0.52)	-0.02 (-0.47)		
MOM				-0.02 (-0.24)				
LIQ					-0.00 (-0.02)			
RMW						0.16 (2.06)		
CMA						-0.11 (-1.12)		
ME							-0.17 (-2.53)	-0.16 (-2.53)
I/A							-0.10 (-1.52)	-0.06 (-0.70)
ROE							0.06 (1.37)	0.02 (0.29)
EG								0.08 (1.05)
Observations	69	69	69	69	69	69	69	69
R2	0.00	0.08	0.30	0.30	0.30	0.36	0.36	0.37

TABLE A.3.21: **Equal-weighted GMB performance - Governance.** We estimate monthly time-series regressions using data from January 2016 to December 2021. The dependent variable is the GMB factor computed as the difference between the equal-weighted returns on the green portfolio and brown portfolios formed by the top (bottom) third of stocks ranked by their greenness score in the previous month ($g_{j,t-1}$). Mkt-Rf is the excess market return. SMB and HML are the size and value factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997). LIQ is the traded liquidity factor of Pástor and Stambaugh (2003). RMW and CMA are the profitability and investment factors of Fama and French (2015). ME, I/A, and ROE are the size, investment, and profitability factors of Hou et al. (2015). EG is the expected growth factor of Hou et al. (2021). Returns are in percent per month. Robust t-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
const	-0.30 (-1.36)	-0.18 (-0.81)	-0.21 (-0.85)	-0.18 (-0.82)	-0.20 (-0.91)	-0.18 (-0.88)	-0.30 (-1.25)	-0.33 (-1.22)
Mkt-RF		-0.08 (-1.61)	-0.04 (-0.51)	-0.08 (-1.37)	-0.04 (-0.85)	-0.13 (-2.16)	-0.04 (-0.57)	-0.03 (-0.38)
SMB			-0.23 (-1.45)	-0.28 (-1.65)	-0.24 (-1.17)	-0.12 (-1.12)		
HML			0.08 (1.98)	0.00 (0.02)	0.09 (1.45)	0.15 (2.19)		
MOM				-0.18 (-1.41)				
LIQ					0.02 (0.20)			
RMW						0.23 (1.94)		
CMA						-0.41 (-1.91)		
ME							-0.13 (-0.80)	-0.12 (-0.76)
I/A							-0.18 (-1.28)	-0.14 (-1.03)
ROE							0.11 (1.62)	0.07 (0.69)
EG								0.07 (0.57)
Observations	69	69	69	69	69	69	69	69
R2	0.00	0.04	0.14	0.22	0.14	0.30	0.21	0.22