ANALYZING THE EFFECT OF ESG LANGUAGE ON THE RISK AND RETURN OF SIN STOCKS

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ABSTRACT

This paper examines the effect of Environmental, Social, and Governance (ESG)-related language on the returns and associated risk for firms situated in sin stock industries. Specifically, this paper strives to answer the question of whether or not tone contained within ESG reports and ESG-related words in annual reports are associated with excess stock returns, volatility, and idiosyncratic risk of select firms in the gambling, alcohol, smoking, and pharmaceutical industries. I select firms on the basis of inclusion in two exchange-traded funds and conduct textual analysis on the disclosures provided by these firms. I find a statistically significant relationship between the percentage of ESG words in annual reports and both the volatility and idiosyncratic risk of the companies in the sample. Additionally, I find that both idiosyncratic risk and volatility decrease as the tone of the language contained in ESG reports becomes more positive. Overall, this paper extends the extant research on ESG disclosures by providing empirical evidence that markets respond to the qualitative information contained in ESG disclosures for firms in sin stock industries.

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TABLE OF CONTENTS

LIST OF TABLES

Dedicated to my parents, Andy and Aimee,

for their abundant support

1. Introduction

Accounting, at its core, encapsulates information that is provided to users of financial data. More specifically, the information that accounting is concerned with is released in the form of disclosures. Firms disclose information, and in turn, markets react to these disclosures and return capital to these firms in the form of investment. While much of the information disclosed by firms is quantitative, markets react to qualitative disclosures as well. For example, there is a vast amount of information contained within corporate disclosures that can be derived from the raw unstructured text. Commonly used disclosure forms are annual reports, quarterly reports, earnings announcements, and call transcripts. But more recently, companies have been electing to disclose information surrounding the companies' Environmental, Social, and Governance (ESG) practices (Lopez de Silanes, McCahery, and Pudschedl, 2020). There are currently no mandatory ESG reporting standards[1], and these reports have contained mostly qualitative information. Therefore, companies can cherry-pick what types of ESG information to include and which details to leave out in these reports.

Firms' ESG initiatives and activities have become increasingly important to investors. Used by both shareholders and stakeholders, ESG provides a framework to evaluate the policies, ethics, and overall sustainability of firms. The Global Sustainability Review of 2020 reports a 54% increase in assets under management (AUM) in sustainable investment from 2016-2020. Additionally, over a third of global AUM is allocated towards investments where ESG factors are considered in portfolio selection

[1] In 2022, the SEC has proposed a requirement for companies to provide investors with more standardized ESG disclosures. As of the time of publication of my study, this proposal had not been implemented. (https://www.sec.gov/news/statement/gensler-statement-esg-disclosures-proposal-052522)

and management.[2] With this increasing focus on ESG factors, many investors believe that companies with strong ESG practices tend to have lower risk and are better prepared for the future. For example, higher ESG ratings are correlated with lower costs of capital, showing that investors appear to respond to ESG ratings (Chen et al., 2023).

Advocates of ESG also argue that strong ESG practices can build a foundation for long-term value creation (Aydogmus, Gülay, and Ergun, 2022). Additionally, ESG performance can affect a company's reputation among consumers, employees, and investors (Brown and Dacin, 1997).

Given that current voluntary ESG disclosures are generally qualitative and that ESG matters to investors, I am examining the empirical question of whether markets react to ESG-related language in a firm's disclosures. Specifically, does ESG-related language affect excess returns, volatility, and idiosyncratic risk?

There is plenty of evidence that suggests that investors pay attention to disclosure language in general (cf. Jones and Shoemaker, 1994; Li, 2010). The increasing prevalence of natural language processing (NLP) has made language analysis less costly and more implementable. NLP can help users of financial data interpret language contained in disclosures through the use of computer algorithms. Moreover, NLP is particularly useful to users of accounting and finance information, as it is able to quickly process and interpret large amounts of data and consequently leads to more informed decisions. For example, NLP can analyze many sources of text such as social media posts, call transcripts, news articles, and company filings (Li, 2010). Then, NLP based

[2] http://www.gsi-alliance.org/wp-content/uploads/2021/08/GSIR-20201.pdf

trading algorithms can make investment decisions much more quickly based on the extraction of certain NLP measures (Frattini et al., 2022). For example, research suggests that investors pay attention to the tone or sentiment included in company disclosures. Many studies show that positive tone in disclosures often leads to better market performance through improved returns and lower risk (Brockman, Li, and Price, 2017; Sadique, In, and Veeraraghan, 2008).

While research has delved into language's effect on company performance and market reactions to disclosures, the effect of ESG language on market measures is largely unexplored. Given the increasing importance of firms' ESG initiatives to investors, this study seeks to establish how informative qualitative ESG disclosures are. My findings build on existing research by establishing that investors appear to react to ESG-related language.

In this study, I focus on firms that operate in industries in which the goods that are provided or the services that are rendered are perceived to be ethical or immoral, often called "sin stocks" in the literature (Kacperczyk & Hong, 2006). Empirically, sin stocks have been shown to outperform the market in terms of returns (Fabozzi, Ma, and Oliphant, 2008). However, evidence has also shown that the market generally neglects these stocks due to social norms, regulatory scrutiny, and litigation risk (Kim and Venkatachalam, 2011). Paradis and Schiehll (2021) also note that sin stocks tend to have lower ESG performance in aggregate and in each of the E, S, and G pillars. Given that ESG is an area in which each company within sin industries can differentiate themselves, I argue that the effects of the language in ESG disclosures are more pronounced for companies already viewed as "sinful" by the market.

I identify 32 companies within sin stock industries based on select exchange-traded funds (ETFs) and analyze the qualitative ESG disclosures of these companies. I hand-collect 10-K filings and voluntary ESG reports released by my sample companies during fiscal years 2019 through 2021 and utilize Python scripts to identify ESG words within these disclosures. Using NLP, I measure word counts, tone, and readability. I then regress excess returns and risk measures on these measured language variables along with several control variables.

First, I find that investors react to the percentage of ESG words included within annual report filings. Specifically, volatility and idiosyncratic risk increase with increases in the percentage of ESG words. However, there is no statistically significant relationship between excess returns and the percentage of ESG words. These results are consistent with the conjecture that investors perceive the higher amount of ESG words as a greenwashing tactic for sin stocks. Furthermore, I also examine the language in discretionary ESG reports that sample firms released. Similar to findings from Sadique et al. (2008), I find a negative and statistically significant relationship between tone within these ESG reports and both volatility and idiosyncratic risk, showing that risk is decreased when positive tone is used in ESG reports. Finally, no significant association is found between the readability of ESG reports and any of the dependent variables.

These results contribute to existing research by providing evidence that markets do respond to ESG disclosures. More specifically, this paper provides evidence that markets do not only respond to third party ESG scores, but also respond to company-provided ESG-related qualitative disclosures. Moreover, these results speak to practitioners as well, as the evidence presented suggests that managers can influence the market by providing more detail and presenting ESG initiatives using more favorable language. Finally, this study also provides additional evidence to policymakers that ESG-related information affects capital markets.

However, the interpretation of my results is limited by a few key factors. First, I examine a small sample of firms in this study. I hand collect the data used in this study and manually run NLP scripts on each individual filing and report. Though this yields accurate measures, it is very time consuming and more suited for a smaller sample. Second, the sample is based on select industries that are considered “sin” industries. Although I specifically chose this industry in order to identify ESG effects, the results may not be generalizable to other industries. Further limiting the sample is the fact that ESG disclosures are not mandatory—many companies within these industries do not disclose ESG reports. Thus, the results may be reflecting a self-selection bias for companies that opt to disclose ESG reports. In other words, the results may be affected by the likelihood that sin stocks that choose to disclose ESG matters might have more positive things to say about their ESG activities.

The rest of this paper is structured as follows. Section 2 provides a literature review and lays out the motivation for the study. Section 3 describes the data and research design. I present and discuss results in Section 4, and conclude in Section 5.

2. Literature Review and Motivation

The Efficient Market Hypothesis asserts that stock prices fully reflect available and relevant public information. Within this hypothesis lies three degrees of efficiency: Weak Form, Semi-strong Form, and Strong Form, which indicate the different degrees to which changes in stock prices reflect varying amounts of information (Fama, 1991).

Researchers over the past couple of decades, however, have noted that stock prices react not only to the content of the information provided, but how the information is presented. An increasing amount of research on behavioral finance has shown that markets are significantly influenced by, among other things, investor psychology, suggesting that information is not the only driver of stock market returns (Kapoor and Prosad, 2017). Behavioral finance maintains that investors react in accordance with human psychology and often stray from making rational decisions. This stream of research finds that investors may either overact or underreact to factors outside of the content of the information provided, thus causing bubbles and corrections in asset prices (Malkiel, 2003). Evidence has shown that as long as humans make investment decisions, markets are often not completely efficient at all times.

2.1. Natural Language Processing

While the degree to which markets reflect information is highly debated, there is no doubt that markets have gained efficiency over the last few decades through the prevalence of technology which has led to both a more connected globe and a faster flow of information (Gu, 2004). More specifically, these technological advances have helped users of financial data extract more information, particularly from textual disclosures. Over the course of history, humans have been using textual analysis in an array of ways to extract and interpret information. More recently, these technological advances have allowed users to gain information much more quickly by using computers, as these machines can process text countless times faster than humans physiologically can. This area of computer science known as natural language processing (NLP) has infiltrated many areas of our life, coming in the forms of voice recognition, online translators, and other machine learning algorithms. This technology which started as a machine used to encrypt secret messages from the Germans in WWII has evolved into smart offices powered by companies like Google (Johri et al., 2021).

Situated within NLP is textual analysis. Amazon Web Services defines text analysis as “the process of using computer systems to read and understand human-written text for business insights.” Li (2010) defines text analysis as the process of aggregating information contained within a large amount of text into a smaller number of manageable variables for further analysis.

The use of textual analysis allows users to collect immense amounts of data and derive previously unobtainable insights from text-heavy documents. For example, computer algorithms can glean insights about one’s personality based on their word selection (Pennebaker & King, 1999). Additionally, investors are using NLP programs to help them derive more insight from public information and consequently use it in their investment decisions. This form of computing uses text inputs to derive inferences from human language (Khurana, Koli, and Khatter, 2023). Investors are also utilizing NLP to trade on increasingly esoteric methods to generate alpha in public markets. One such method is algorithmic trading at very high frequency. These algorithms use a vast array of information, both quantitative and qualitative (Grindsted, 2021). Since these trades are based on algorithms, this investment strategy reduces the influence of human emotion and heuristics, and thus aims to minimize error resulting from human biases. Many models also incorporate various measures of textual characteristics as well. Given that text can convey information more than just the content included in the text itself, investors have started to research and build predictive models which form the bases of investment strategies that attempt to outperform passive indexes (Vargas, de Lima, and Evsukoff, 2017).

The extant research in accounting and finance has also employed textual analysis in exploring the various facets of language that the market reacts to, which I discuss in greater detail below.

2.2. Readability of Financial Disclosures

Several studies have delved into the relationship between the readability of a company's disclosures and the company's stock returns. Specifically, the literature tends to hold that more readable reports tend to produce stronger reactions from investors, both positive and negative. Conversely, investors' reactions are relatively weaker when disclosures are less readable (Rennekamp, 2012). These results are consistent with the conjecture that readable disclosures are associated with managers being more transparent with their actions, and on the other hand, investors view less readable disclosures as less reliable. Moreover, Rennekamp's study shows that report readability is related to positive earnings persistence. In other words, firms that have more complex wording in their annual reports tend to have less consistent earnings performance. Along these lines, You and Zhang (2009) find that investors display weaker reactions to longer 10-K filings, bolstering the argument that investors favor information that is straightforward and easy to comprehend. Consistently, when examining disclosures from a preparer perspective, evidence suggests that managers seek to structure annual reports in ways that hide unfavorable information from investors (Li, 2008).

Given that the market pays less attention to less readable 10-K filings, investors often seek and turn to alternate forms of information. For example, Tan, Wang, and Zhou (2014) show that when disclosures are less readable, investors appear to rely more heavily on disclosure tone. Additionally, their research displays that investors are likely to seek outside information (i.e., information that is not disclosed in the 10-K) more heavily than information contained within the 10-K, as well as weight outside information more heavily in investment decisions. Overall, this research on readability suggests that investors react more favorably to information when it is readable.

2.3. Tone of Language in Financial Disclosures

In addition to readability, accounting academics have begun to examine the tone of language contained in corporate disclosures such as earnings calls, proxy statements, and annual reports to develop predictions about stock price movements. These studies use NLP to extract textual components and measure sentiment. Although the literature on tone is more mixed than the current evidence on readability, researchers do tend to agree that tone often does have a material impact on stock prices, leading company disclosure tone to be an increasingly large focal point in academic literature.

Cho, Roberts, and Patten (2010) compare stock returns with both tone of disclosure and the certainty contained in management's language. They find that when disclosure language has a bias toward optimism with lower scores for certainty, poor stock performance often ensues. Hanley and Hoberg (2010) also find that investors also react to tone in prospectuses for IPO companies. This study finds that when there is a bias toward positive tone contained in the “risk factors” section of a company’s IPO prospectus, the IPO is priced higher, signifying that the perceived riskiness of the IPO is lower.

Investors also pay close attention to management’s tone in earnings calls. For example, Huang, Teoh, and Zhang (2014) find that when management is abnormally positive during these releases, stock prices often trend upward after the earning release. However, during the subsequent one to two quarters, a delayed negative reaction often follows. Similarly, Cohen, Malloy, and Nguyen (2020) find that when sentiment changes over a reporting period, negative returns often follow. The aforementioned study looks at other change variables such as disclosure length and finds that overall, returns tend to be higher when report length remains relatively constant.

Sadique et al. (2008) examine the effect of tone on stock returns and volatility and find that positive tone often increases returns and decreases volatility, while negative tone decreases stock returns and increases volatility. On the other hand, Malaquias & Júnior (2021) analyzed the effect that positive tone in management reports on stock return volatility of Brazilian firms from 2011-2020. In this case, they found that companies with higher positive tone do not necessarily create lower stock volatility.

Tone and returns have also been studied in international exchanges as well. For example, Brockman et al. (2017) find that stock returns in the Hong Kong Stock Exchange increase with measures of positive tone exhibited by managers in company conference calls.

Note that the heightened focus on tone is also common among practitioners. For instance, investors have increasingly turned to computer algorithms to analyze tone across a broad variety of company disclosures. For example, Platforms like Bloomberg and Factset analyze the text contained within earnings call transcripts and assign sentiment scores to company disclosures.[3] Doing so helps provide investors with information about the overall attitude reflected by management.

Although the literature on tone is more mixed than the current evidence on readability, researchers do tend to agree that tone often does have a material impact on stock prices, leading company disclosure tone to be an increasingly large focal point in academic literature. Additionally, studies have measured tone across various types of corporate disclosures, including earnings calls, proxy statements, and annual reports. I extend this line of research by looking at ESG-related disclosures, which have become more prevalent and important over the past decade.

2.4. Environmental, Social, and Governance (ESG) Factors

In recent years, investors have also started to place a high emphasis on environmental, social, and governance (ESG) factors in investment decisions. Although ESG has been around for decades, public perception of the term and the use of these factors in investment decisions has recently skyrocketed. One such event triggering this rise was the global financial crisis in 2008, which highlighted a pitfall in financial regulation, in humanitarian ethos, and institutional values. In the following years, investors have arguably become more sensitive to socially beneficial investments (Puaschunder 2016).

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[3] https://go.factset.com/marketplace/catalog/product/sentiment-and-fundamental-indicators

ESG is often used as a measure of long-term sustainability, and the prevalence of ESG measures allows investors to make more informed decisions by evaluating companies based on the risk of ESG failure and long-term viability. Moreover, ESG-focused companies have been found to have sustainability strategies that often bring the company future cost savings, lower employee turnover, increased operational efficiency, and better risk management (Boffo and Patalano, 2020). According to Camilleri (2018), ESG issues are an important focus for companies to remain competitive and raise investment. Because of this, many investors have designed investment decision rules around ESG, consistent with the belief that companies focusing on or emphasizing their ESG practices realize superior returns. Empirically, an increasing percentage of investment has been allocated towards "ESG", "socially responsible" and "sustainable" investments over recent years. Specifically, institutions are pouring an increasing percentage of their capital into ESG-related investments. According to a recent report published by the Global Sustainable Investment Alliance, the total assets under management (AUM) of sustainable investments has increased 54% from $22.9 trillion to $35.3 trillion between 2016 and 2020. Moreover, 35.9% of global AUM has been allocated towards ESG investment in 2020, compared to 27.9% in 2016. In the U.S., this change has been even more drastic, springing from 21.6% in 2016 to 37.9% in 2020.[4]

Given that investors are pouring an increasing amount of capital into these funds, along with the positive public perception of socially responsible actions of corporations, public companies are currently under immense pressure not only from both shareholders and stakeholders to show engagement in ESG-related activities and initiatives. At the

[4] http://www.gsi-alliance.org/wp-content/uploads/2021/08/GSIR-20201.pdf

very least, companies are incentivized to appear more ESG-friendly to bolster the company's image and share price. To this end, the vast majority of companies in the S&P 500 are now choosing to disclose information surrounding ESG matters.[5] Presumably, if a company can appear just slightly more sustainable, it could improve long-term financial performance through increased investment. While it is less frequent for companies to engage in extreme or fraudulent greenwashing practices today, unstandardized and voluntary ESG reporting practices create a grey area that allows for misleading ESG disclosures (Gatti, Seele, & Rademacher, 2019).

Appearing more ESG-friendly is not necessarily consistent with actually creating a better future for the world. Corporations ranking high on any ESG index may not always act the most socially- or environmentally-responsible. Companies can ostensibly appear to be more socially responsible without actually making a positive impact on the world, in order to sustain higher share prices or to be lumped into indexes where passive investment will flow. For example, on S&P 500 ESG index, TSLA was left out during the index rebalancing in May 2022, while oil giant, Exxon was left in.[6]

ESG ratings have also been criticized in both academic literature and in the investment world mainly because ESG ratings for one firm can be vastly different across rating providers. This phenomenon is known as rating divergence (Chatterji et al., 2016; Billio et al., 2021; Gibson, Kruger, and Schmidt, 2021). Like credit ratings, ESG these scores give investors a quick screening method to vet out investment options. However,

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[5] https://www.thecaq.org/sp-500-and-esg-reporting

[6] https://www.cnbc.com/2022/05/18/why-tesla-was-kicked-out-of-the-sp-500s-esg-index.html#:~:text=It%20said%20that%20Tesla's%20%E2%80%9Clack,%2C%20California%2C%20affected%20the%20score.

rating agencies use different frameworks and methodologies rate companies. By having differences in foundational theory and ESG definitions, ratings often diverge (Chatterji et al., 2016)

One big issue with ESG scores is that ESG scoring is not standardized, as index providers use subjectivity and discretion when picking ESG investments. For example, the president of Morgan Stanley's Calvert Research Group still included Tesla in their index despite being taken off of the S&P's ESG index, believing the company was more responsible than firms with higher ratings.

Given that there is a relatively high variation in ESG scores and that these scores are inherently noisy, investors have good reason to pay attention to ESG-related company disclosures. Recent and preliminary evidence is provided by Chen et al. (2022), who find a negative relationship between the presence of ESG disclosures and return volatility. Their results indicate that increasing ESG disclosures could play a key role in alleviating volatility in returns. Moreover, Ghoul et al. (2022) find that positive ESG performance is negatively associated with a company's cost of capital. The study also displays that sin stocks carry higher costs of equity.

My study extends the extant research on both qualitative disclosures and market perceptions of ESG information by exploring how markets react in particular to ESG disclosures that firms provide. In particular, I focus on industries in which ESG disclosures are expected to have a more substantial impact on market reactions.

2.5. Sin Stocks

The label “sin stocks” typically refers to companies that operate in industries that are traditionally viewed as morally questionable or unethical, often including gambling, alcohol, and tobacco companies (Kacperczyk & Hong, 2006).

Although companies in sin industries do not get high praise from advocates for ESG practices, these companies can use ESG and sustainability disclosures to signal practices and vouch for their right to exist in spite of their questionable core operations. Moreover, companies, including and particularly those situated and sin industries, have increasingly started to publish ESG reports to enhance their legitimacy. For sin companies, the publishing of an ESG report can help the company paint a better representation of itself by showing its positive contributions to society, despite the fact that core operations also cause harm (Dhandhania and O’Higgins, 2022).

Because these companies primarily engage in activities that are seen as controversial and often unethical, their stock prices can be negatively affected. Investors often boycott buying these companies which compresses their multiples (Colonello, Curatola and Gioffré, 2019). That is, investors often discount the value of these companies because of the ethical considerations of the industry. However, this means that any positive ESG disclosures could potentially offset this negative impact, leading to increased returns. Further, these companies are often subject to greater regulatory risks than other industries. For example, within the tobacco industry, companies are often subject to greater taxes, advertising restrictions, and other regulatory pressures (Henriksen, 2012). If a company appears, through its ESG disclosures, to be dedicated to responsible practices, investors might realize greater returns through the mitigation of risks intrinsic to these sin industries. Companies in this industry are also subject to the risk of changing consumer preferences. Specifically, consumers that are more socially or environmentally conscious might be more likely to support companies through their purchases that demonstrate a commitment to sustainable or responsible practices. If a company appears to care about the environment or social issues through its ESG disclosures, these ESG conscious consumers might be more inclined to support the company, leading to positive financial performance (Boufounou et al., 2023).

Specific to sin stocks, the results are generally mixed. Paradis and Schiehll (2021) observe that sin stocks generally have lower ESG scores in aggregate (as well as individual E, S, and G component scores), suggesting that these companies are inherently exposed to higher levels of risk relating to ESG issues. Similarly, Horn (2023) analyzes the relationship between ESG ratings on idiosyncratic risk. Overall, the study finds that ESG ratings are negatively related to idiosyncratic risk. That is, when ESG scores improve, idiosyncratic risk decreases. Furthermore, this effect is consistent for companies situated in sin industries and proves that the negative relationship persists.

On the other hand, Ghouma and Hewitt (2019) find a negative association between CSR performance and abnormal returns within the sin stock industries. They conjecture that CSR activities may signal that managers of these sin companies are covering up even worse things that their firms are doing, resulting in an even worse view of these firms. Vanhamme and Grobben (2009) similarly suggest that markets see through the CSR claims of sin firms to counter negative publicity.

2.6. Predictions

Taking all the current research into consideration, I explore ESG disclosures more deeply and examine whether the language in ESG disclosures of sin stocks affects stock performance. Particularly, I consider the amount of ESG language in a sin firm's annual report, as well as develop measures of tone and readability in ESG reports. I then associate these language measures with abnormal returns and measures of risk.

Given the current literature on how markets react to ESG performance overall, I do not make any directional predictions as to how tone and amount of ESG language are associated with market measures.

More specifically, I expect that the amount of ESG language in annual reports could either mitigate risk (and result in more positive market reactions) or conversely be perceived as a form of greenwashing, leading to the opposite outcome. Therefore, I make no directional prediction for this measure.

Similarly, on one hand, it may seem reasonable that more positive tone in ESG reports could reduce risk and lead to excess returns, just as positive tone in other disclosures has a risk-mitigating effect and is often associated with increased subsequent returns. However, since these are sin stocks, investors might just think that positive tone in ESG disclosures may be an attempt to mask the company's risk, which could lead to an opposite effect. Therefore, I do not make any directional prediction with regard to tone.

Finally, consistent with prior research surrounding annual reports, I predict that more readable ESG reports could be correlated with a stronger reaction in price movements in either direction, but make no predictions regarding readability and risk.

3. Methodology

3.1. Sample Selection

I focus my analysis on sin stocks and identify companies that have disclosed ESG reports within sin industries in the years 2019 through 2021. I limited my sample to these years since the release of ESG reports is a relatively recent phenomenon. I relied heavily on the Betting, Alcohol, and Drug (BAD) exchange-traded fund (ETF), which tracks the performance of 52 gambling, alcohol, and pharmaceutical companies.[7] Note that I also include pharmaceutical companies in my sample because, although these companies are not typically classified as sin stocks by the prior literature, many consider them to be controversial due to high drug prices and the marketing of certain prescription drugs—which is one of the reasons why pharmaceutical firms are part of the BAD ETF. Additionally, I selected companies from the VanEck gaming ETF, which tracks 25 gambling companies.[8] In addition to using these two ETFs, I also did a broad sweep of companies within each industry to uncover firms that are not included in these ETFs. For example, I wanted to include tobacco companies (which are included in the traditional definition of sin stocks but were not covered in either of the two ETFs) in my sample, so I selected as many as I could find within the industry.

After identifying potential sample firms based on industry, I required sample companies to have published at least one ESG report in my sample timeframe. To do this, I scanned investor relations pages and conducted Google searches to find and hand-collect ESG reports. This significantly reduced my sample size as many companies in

[7] https://badinvestmentco.com/bad-etf/
[8] https://www.vaneck.com/us/en/investments/gaming-etf-bjk/

these industries have not developed the custom of publishing ESG reports. After considering 98 firms across the four industries, I narrowed down my final sample to 32 firms.

3.2. Data Collection

I use the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database to find 10-K and 20-F filings for each of the sample firms. EDGAR is the primary database for companies that are required by law to file forms with the SEC. These public forms are uploaded to EDGAR for the public to access to help users of financial information make more informed decisions. Additionally, I use company investor relations pages to download annual reports published in PDF formats when reports were not found on the SEC's EDGAR database. I also used investor relations pages to download company ESG reports in pdf form.

I restrict these reports and filings to firms' fiscal years between 2019 to 2021 (inclusive) and measure the extracted independent variables against the dependent variables found in the subsequent year. I focus on recent years as ESG reporting is a relatively new practice and has not been adopted by all corporations.

3.3. Model and Variables

I run the following model to test the association between ESG language and market measures.

$$DEPVAR_t = INDVAR_{t-1} + ROA_{t-1} + Leverage_{t-1} + Earnings\ Surprise_{t-1} \qquad (1)$$

My dependent variables of interest (DEPVAR) include annual excess returns, volatility, and idiosyncratic risk. The excess return variable is calculated by the Center for Research in Stock Prices (CRSP) as a stock's annualized return less the annual return on a value-weighted index. Volatility and idiosyncratic risk variables are collected from the WRDS Beta Suite. Volatility represents the volatility of the realized returns of a company's stock, while idiosyncratic risk is defined as the difference between realized and expected returns based on a 3-factor Fama-French risk model (Ang et al., 2006).

I use three measures as my independent variables (INDVAR) to capture different facets of ESG language: percent of ESG words in the annual report, tone of the ESG report, and readability of the ESG report. All these independent variables are measured the in the year preceding (year t-1) and the dependent variables (year t).

I measure the number of ESG words as a percentage of total words in each annual filing. This variable is a measure of the extent to which companies include ESG-related language in its annual reports. I identify ESG words using a self-developed dictionary of 37 ESG-related words and phrases based on hand selected words found in ESG glossaries developed by two law firms: Vinson & Elkins[9] and the Zeidler Group[10]. I imported a Python library known as Beautiful Soup which allows a script to parse through an html file. My Python script also contained my dictionary of 37 words in the form of a Python list. Broken down, environmental (E) words accounted for 37.8% of the dictionary; social (S) words made up 35.1%, governance (G) words made up 5.4%, and other (O) made up 21.6%. For a complete listing of these words, refer to the Appendix. Running this code allowed me to get the total number of words in the annual report, the total number of ESG-related words, and a count of each appearance of the individual words contained in the dictionary. I sum the occurrences of these words in a company's annual report or its

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[9] https://www.velaw.com/esg-glossary/

[10] https://zeidler.group/insights/esg-glossary/

10-K or 20-F filing, whichever is available. I then scale this number by the total number of words in the report.

Additionally, I break down the percentage of E, S, G, and O words to see if any particular disaggregated categories drive the results.

While ESG language is collected from companies' annual reports, my next two measures on tone and readability are gathered from ESG reports.

I evaluate the tone contained within ESG reports by analyzing the frequency of both positive and negative words. Consistent with extant research, I rely on a dictionary developed by Loughran and McDonald (2011) that has been commonly used to analyze the sentiment or tone of corporate disclosures.[11] This dictionary contains a plethora of words that are categorized as "positive" or "negative" based on their use in the financial domain. For example, words like "successful", "profitable", and "growth" are categorized as positive, while words like "loss", "liabilities", and "risky", are categorized as negative words. Using this dictionary and a textual analysis tool written in Python that gathers the frequency of both positive and negative words, I use one primary variable as my measure of tone: the difference between positive and negative words scaled by the total number of positive and negative words.

To measure the readability of ESG reports, I calculate the Fog index.[12] This formula, created by Robert Gunning, is a commonly used formula for assigning text a readability score as a function of words per sentence and the number of syllables per word. This score is communicated as a grade level or the number of years of education a

[11] https://sraf.nd.edu/loughranmcdonald-master-dictionary/
[12] Although there are many different measures of readability that researchers employ (and each calculation might yield slightly different results), the Fog Index is a widely used calculation in this area of research.

reader would need to easily comprehend the text. So, a higher score means the text is more sophisticated and difficult to read.

The formula for determining the score is the following:

$$Fog = (\text{average sentence length} + \text{percentage of complex words}) * 0.4 \qquad (2)$$

Average sentence length is the total number of words in the ESG report divided by the number of sentences. Complex words are based on syllable count and are defined as words with three or more syllables. In this equation, the percentage of complex words is defined as the number of complex words divided by the total number of words analyzed.

I ran a different Python script to measure tone and readability. I used two important Python libraries: pdfminer and pysentiment2. The first, pdfminer is a useful tool developed in Python that helps a allows convert a .pdf file into a .txt file and subsequently execute a textual analysis of words contained in the pdf. Next, pysentiment2 is a package used for sentiment analysis and allows a user to use certain lexicon-based dictionaries such as the dictionary developed by Loughran and McDonald (2011) that I use in my study. This script also contained the function to determine the readability of each ESG report using the calculation provided earlier.

Additionally, I include variables that are potentially correlated with my independent variables and are known to affect market reactions to information. I include return on assets (ROA) and Leverage, taken from Compustat, and the Earnings Surprise (the difference between actual EPS and the consensus analyst forecast of EPS), taken from CRSP.

4. Results and Discussion

4.1. Descriptive Statistics

Table 1 presents the descriptive statistics for my full sample.

TABLE 1
Descriptive Statistics

Variable	N	Mean	Median	Std Dev	Min	Max
%ESG Words	95	0.028	0.015	0.028	0.002	0.125
%E Words	95	0.009	0.006	0.009	0.000	0.045
%S Words	95	0.012	0.009	0.011	0.001	0.061
%G Words	95	0.000	0.000	0.000	0.000	0.003
%Other ESG Words	95	0.007	0.002	0.012	0.000	0.052
Tone	79	0.113	0.091	0.166	-0.205	0.495
Readability	79	9.760	10.246	4.020	2.444	36.520
Total Assets ($MM)	90	47.80	24.53	60.86	0.41	236.65
Total Revenues ($MM)	90	16.28	8.48	20.77	0.27	93.78
Net Income ($MM)	86	2.69	0.44	4.98	-2.07	21.98
ROA	86	3.4%	3.6%	10.1%	-37.4%	38.5%
Leverage	90	69.5%	64.0%	27.8%	17.4%	151.5%
Earnings Surprise	64	12.6	2.3	101.3	-102.8	600.0
Excess Return	74	-4.8%	-6.8%	40.0%	-105.8%	142.4%
Volatility	51	10.2%	8.0%	5.0%	4.4%	21.3%
Idiosyncratic Risk	51	8.4%	7.1%	3.6%	3.6%	16.9%

The average proportion of ESG words within the annual reports sampled was 0.028%, ranging from 0.002% to 0.125%. Unsurprisingly, given the length and amount of information disclosed in the annual filing, the percentage of ESG words is a very small percentage of overall words. Note that the overall length of the annual report has been increasing over time, with one study showing an increase of more than 100% between 1996 and 2013 (Dyer, Lang, and Stice-Lawrence, 2017). The same study also indicated that much of the annual report contains boilerplate language, so even though the percentage of ESG words seems economically small in magnitude, changes in the amount of this language may have a potentially significant impact on market perceptions.

The breakdown of the ESG words in the annual report consists mostly of S words with an average of 0.012% of total words in the annual report, followed by E words (0.009%) and other words (0.007%) that are ESG-related but not specifically tied to E, S, or G activities per se (examples include “sustainability” or “integrated reporting”). Although one would expect G words to be more prominent in annual reports, I exclude governance-related words that are likely to be boilerplate, such as “board of directors,” “auditors,” or “compensation,” and instead I include words such as the acronym, “SASB” and “business ethics.” Thus, the count of G words in the annual filings for purposes of my study is small in magnitude.

In terms of the language metrics, the mean score for Tone contained in the ESG reports was 0.113 and ranged from -0.205 to 0.495, indicating that ESG reports contained more positive tone than negative tone words on average. The average Fog index of annual reports, which is my measure of Readability, is 9.760, suggesting that the average annual filing requires almost 10 years of education to be able to comprehend the content of the report. Other studies looking at the Fog index of a wider variety of annual filings report indices of around 18-20 (Li, 2008; Lo, Ramos, and Rogo, 2017), suggesting that annual filings of the companies in my sample are overall simpler to read than the annual filing of the average public firm.

Looking into market measures, the excess return for the sample ranged from -0.081% to 0.162% and averaged 0.027%. The average idiosyncratic risk was 0.084 and spanned from 0.036 to 0.169. Finally, the average volatility was 0.102 and ranged from 0.044 to 0.213

Firms within the sample also had an average ROA of 0.03416. The minimum ROA was -0.3743 and the maximum was 0.3849. Next, the sample had an average leverage ratio of 0.695, ranging from 0.173 to 1.514.

4.2. Analysis of ESG Language in Annual Filings

Presented in Table 2 are the results of the tests of association between market measures and the ESG language in the annual filing.

TABLE 2
Percent of Total ESG Words in Annual Filing and Market Reactions

	(1)	(2)	(3)
VARIABLES	*Excess Return*	*Volatility*	*Idiosyncratic Risk*
%ESG Words	-0.696	0.709***	0.528***
	(0.684)	(0.004)	(0.004)
ROA	1.170***	-0.294***	-0.208***
	(0.000)	(0.000)	(0.001)
Leverage	-0.012	0.041	0.014
	(0.926)	(0.216)	(0.601)
Earnings Surprise	0.000	0.000***	0.000***
	(0.534)	(0.000)	(0.002)
Constant	-0.047	0.078**	0.077***
	(0.660)	(0.017)	(0.005)
Observations	59	44	44
R-squared	0.095	0.351	0.319

Robust p-values in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 2, Column 1, the coefficient on %ESG Words is negative but not statistically significant, suggesting that either the amount of ESG language in an annual report is not a significant driver of subsequent excess returns, or that the market has already priced in the perceived ESG activities of these companies in sin industries. On the other hand, there is a positive and significant relationship between %ESG Words and Volatility (Table 2, Column 2). This result indicates that companies are able to successfully portray themselves as being less risky through the use of more ESG words in their annual reports. It is plausible the number of ESG words is a signal of how much ESG activity a firm actually engages in, but since I have no way of measuring the actual ESG activity, I cannot categorically make the claim beyond what companies disclose through language in their annual reports.

This finding is contrary to that of Chen et al. (2022), who found a negative relationship between ESG disclosures and return volatility. This disparity is likely due to the nature of the companies used in the sample. Since the firms I study are sin stocks, higher usage of ESG words in annual reports could suggest an effort to become more environmentally or socially responsible to counteract any negative reputational impacts of their core businesses, which are arguably unique to sin stocks. In the case of these sin companies, consistent with the results of Vanhamme and Grobben (2009), it is more likely that investors may either be skeptical about or even not see any merit, in the firm's ESG initiatives. In other words, investors might believe that firms are using ESG language as a greenwashing tactic in an attempt to mask the negative aspects of the company, leading to increased volatility.

Likewise, in Table 2, Column 3, there is a statistically significant relationship between the %ESG Words in an annual report and the idiosyncratic risk of the company in the subsequent year. As idiosyncratic risk is a similar measure to volatility, this finding supports the possibility that investors perceive the use of ESG language in sin stocks' annual reports as management's attempt to obfuscate other risks and negative facets of the company, and thus skepticism increases with greater ESG language.

To further understand the relationship between ESG words and the dependent variables of interest, I run the same regression as in the previous table but break out the percent of ESG words into the percent of E, S, G, and Other ESG-related words. Results are presented in Table 3.

TABLE 3
Percent of E, S, and G Word Groups in Annual Filing and Market Reactions

	(1)	(2)	(3)
VARIABLES	*Excess Return*	*Volatility*	*Idiosyncratic Risk*
%E Words	4.176	-4.113	-3.447*
	(0.721)	(0.125)	(0.089)
%S Words	-4.896	4.229**	3.449**
	(0.562)	(0.040)	(0.029)
%G Words	-10.658**	-13.616	-12.130*
	(0.011)	(0.123)	(0.065)
%Other ESG Words	13.287	2.335	1.357
	(0.623)	(0.689)	(0.761)
ROA	0.939***	-0.261***	-0.182***
	(0.001)	(0.001)	(0.003)
Leverage	-0.016	0.019	-0.005
	(0.898)	(0.371)	(0.737)
Earnings Surprise	-0.000	0.000***	0.000***
	(0.923)	(0.000)	(0.000)
Constant	-0.047	0.097***	0.095***
	(0.733)	(0.000)	(0.000)
Observations	59	44	44
R-squared	0.120	0.480	0.502

Robust p-values in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The coefficients on %E Words are statistically insignificant in Table 3, Columns 1 and 2, suggesting no relationship between environmental language and both excess returns and volatility. However, there is a marginally significant negative relationship between %E Words and idiosyncratic risk as shown in Column 3, suggesting that investors might view hints of environmental initiatives as diminishing company-specific risk in sin stocks.

Table 3, Columns 2 and 3 show statistically significant and positive coefficients on %S Words (i.e., social responsibility, ethics, and others). These coefficients suggest that firms that use more “S” words are more likely to be associated with higher levels of volatility and idiosyncratic risk, potentially caused by investors perceiving that sin stock companies that emphasize social initiatives as having higher risk relative to companies within these industries that do not have as much socially-related language in their annual reports. There is no statistically significant association between %S Words and excess returns (Table 3, Column 1).

Finally, although I find significantly negative associations between “G” words and both excess returns and idiosyncratic risk, the interpretation of my results is limited by the small sample of governance words included in the dictionary. Because of this, these results should be interpreted with caution.

I extend my analysis by examining changes in the amount of ESG language across annual filings. In this analysis, I am able to use each firm as its own control and determine whether the increased usage of ESG language is perceived positively or negatively by the market. Results of these tests are presented in Table 4.

TABLE 4
Change in Percent of ESG Words in Annual Filing and Market Reactions

VARIABLES	(1) *Excess Return*	(2) *Volatility*	(3) *Idiosyncratic Risk*
Δ %ESG Words	-1.106	0.804***	0.607***
	(0.369)	(0.000)	(0.000)
ROA	0.785*	-0.396***	-0.270***
	(0.065)	(0.001)	(0.000)
Leverage	0.340	0.042	0.013
	(0.190)	(0.273)	(0.677)
Earnings Surprise	0.000	0.000***	0.000***
	(0.728)	(0.000)	(0.000)
Constant	-0.254	0.084**	0.082***
	(0.219)	(0.016)	(0.008)
Observations	35	27	27
R-squared	0.131	0.614	0.559

Robust p-values in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Consistent with my earlier findings, the coefficients on the change in the percentage of ESG words are statistically significant and positive in Table 4, Columns 2 and 3 (while the coefficient on this variable is negative but not significant in Column 1). These results suggest that as firms in sin industries increase the number of disclosures pertaining to ESG activities, market perception of risk increases. This finding builds on the research of Cohen et al. (2020), which studies whether changes in language within an annual report are associated with the company's subsequent returns. Although their study finds that change in language often dampens subsequent returns, my study shows that increases in ESG language frequency in annual reports have negative consequences and are associated with subsequently increased volatility and idiosyncratic risk. Unlike Cohen et al. (2020) however, I find no results for excess returns.

The rest of my analysis focuses on language in ESG reports.

4.3. Analysis of Tone in ESG Reports

Presented in Table 5 are results of regressions of market measures on the tone of the language used in ESG reports.

TABLE 5
Tone of Language in ESG Report and Market Reactions

	(1)	(2)	(3)
VARIABLES	*Excess Return*	*Volatility*	*Idiosyncratic Risk*
Tone	0.413	-0.134**	-0.103**
	(0.174)	(0.023)	(0.017)
ROA	1.177***	-0.191***	-0.134***
	(0.000)	(0.009)	(0.009)
Leverage	0.153	0.006	-0.012
	(0.452)	(0.888)	(0.698)
Earnings Surprise	0.000	0.000***	0.000***
	(0.941)	(0.000)	(0.000)
Constant	-0.238	0.122**	0.110***
	(0.149)	(0.011)	(0.003)
Observations	50	38	38
R-squared	0.197	0.415	0.413

Robust p-values in parentheses
*** p<0.01, ** p<0.05, * p<0.1

First, in Table 5, Column 1, the coefficient on Tone is positive but statistically insignificant, suggesting no discernible relationship between tone and excess returns. Contrary to Brockman et al. (2017), and Huang et al. (2014) that find positive relationships between tone contained in company conference calls and the company's subsequent returns, my study does not find a significant relationship between ESG report tone and excess returns, particularly for sin stocks. One potential reason is that investors may not focus as much on ESG reports relative to the mandatory annual and quarterly reports. Although based on prior research, ESG reports could be informative for investors, but it does not appear that returns are affected by the language in these reports for sin stocks.

On the other hand, there is a notable negative and statistically significant relationship between tone and risk, as evidenced by the coefficients on Tone in Table 5, Columns 2 (volatility) and 3 (idiosyncratic risk). These results are consistent with the conjecture that more positive tone in ESG reports might have a dampening effect on the subsequent volatility of a company's returns. This finding is consistent with Sadique et al. (2008), who find that positive tone in company press releases is associated with lower stock return volatility. Management might use this tactic to mask the overall risk of the company, particularly within sin industries. Consistent with the management obfuscation hypothesis, managers could increase in positive tone to reduce volatility by maintaining a positive public image or avoiding investor backlash simply through language. Once more, to the extent that the tone of the ESG report is a representation of actual ESG initiatives, it is possible that investors are correctly reacting to the reduction of risk within these companies. However, I am unable to distinguish between the two explanations.

4.4. Analysis of ESG Report Readability

Finally, I examine how the readability of the ESG report is associated with market measures. The results contained within Table 6 show no statistically significant relationships between the readability of an ESG report and the excess returns (Column 1), volatility (Column 2), or idiosyncratic risk (Column 3). These findings suggests that investors' behavior is not impacted by the readability of discretionary ESG reports, particularly for companies within sin industries.

TABLE 6
Readability of ESG Report and Market Reactions

	(1)	(2)	(3)
VARIABLES	*Excess Return*	*Volatility*	*Idiosyncratic Risk*
Readability	-0.015	0.001	0.000
	(0.306)	(0.822)	(0.944)
ROA	1.304***	-0.324***	-0.229***
	(0.000)	(0.000)	(0.001)
Leverage	0.018	0.051	0.021
	(0.878)	(0.142)	(0.399)
Earnings Surprise	-0.000	0.000***	0.000***
	(0.965)	(0.000)	(0.004)
Constant	0.049	0.071	0.076*
	(0.765)	(0.175)	(0.064)
Observations	50	38	38
R-squared	0.178	0.314	0.298

Robust p-values in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5. Conclusion

This paper builds on current literature in accounting and finance by examining the intersection between natural language processing research and ESG research. In this study, I examine 32 firms categorized as sin stocks and test the association between language characteristics (magnitude, tone, and readability) of ESG language and market measures (excess returns, volatility, and idiosyncratic risk). Using a self-constructed dictionary of ESG terms and established measures of tone and readability, I find significant associations between the amount of ESG words in the annual filing and risk. Similarly, I provide evidence that risk is significantly associated with the tone within ESG reports. However, I find no significant relationship between any of the market measures with readability.

In examining the relationship between ESG word frequency and the market measures, I find no significant relationship is found between ESG word frequency and excess returns. However, both risk measures (volatility and idiosyncratic risk) increase with ESG word frequency, suggesting that perceived risk increases when more ESG language is reported in a firm's annual filings. Although this result is contrary to the findings of both Chen et al. (2022) and Ghoul et al. (2011), I conjecture that for sin stocks in particular, investors may view ESG word use as a tactic that masks the true risk of the firm rather than a sincere and true focus on increasing ESG activities, consistent with the arguments made by Vanhamme and Grobben (2009). In turn, this might be why risk increases with the amount or magnitude of ESG language.

I also study ESG reports in addition to the required annual filings with the SEC. I find that investors react to the tone contained in ESG reports Specifically, my results show that a more positive tone contained within ESG reports is associated with lower volatility and idiosyncratic risk.

Together, the results of this paper suggest that markets react to ESG language. However, my study has a few limitations. First, there may be a self-selection bias, since I focus on sin stock companies that opted to release ESG reports, which are not mandatory disclosures. Further, the sample size is small given the hand-collection of data and lack of computing power. Finally, the reason why is less discernible from my data and research design. Accordingly, future research can build on my results by exploring when ESG language in annual reports can have contrary effects—that is, when investors react positively vs. negatively to ESG language. Additionally, it would be helpful to understand why investors may react differently to language characteristics in required disclosures versus discretionary disclosures (such as ESG reports). To this end, the same research question employed in this study should be examined once more when ESG disclosures become more prevalent and mandatory across all public companies.

APPENDIX

ESG Dictionary

Environmental (E) Words	Social (S) Words
environmentally carbon neutral environment environmental environmental justice net zero carbon emissions decarbonization greenhouse gasses paris agreement climate climate change waste management energy efficiency	social social responsibility CSR corporate social responsibility community impact investing double bottom line triple bottom line social impact responsible human rights ethical pay equity diversity
Governance (G) Words	**Other (O) Words**
SASB business ethics	sustainable ESG sustainability GRI GRI standards integrated reporting sustainability report global reporting initiative

BIBLIOGRAPHY

Ang A., R. J. Hodrick, Y. Xing & X. Zhang, (2006). The cross-section of volatility and expected returns, *Journal of Finance*, 61, 259-299.

Asay, H. S., Elliott, W. B., & Rennekamp, K. (2017). Disclosure readability and the sensitivity of investors' valuation judgments to outside information. *The Accounting Review*, 92(4), 1–25.

Aydoğmuş, M., Gülay, G., & Ergun, K., (2022). Impact of ESG performance on firm value and profitability. *Borsa Istanbul Review*, 22, 119-127.

Billio, M., Costola, M., Hristova, I., Latino, C., & Pelizzon, L. (2021). Inside the ESG ratings: (Dis)agreement and performance. *Corporate Social Responsibility and Environmental Management*, 28(5), 1426– 1445.

Boffo, R. & R. Patalano (2020). ESG Investing: Practices, Progress and Challenges. *OECD Paris*.

Boufounou, P., Moustairas, I., Toudas, K., & Malesios, C. (2023). ESGs and customer choice: Some empirical evidence. *Circular Economy and Sustainability*, Forthcoming.

Brockman, P., Li, X., & Price, S.M. (2017). Conference call tone and stock returns: Evidence from the stock exchange of Hong Kong. *Asia-Pacific Journal of Finance Studies*, 5(46), 667-685.

Brown, T. J. & Dacin, P. A. (1997). The company and the product: Corporate associations and consumer product responses. *Journal of Marketing*, 61(1), 68–84.

Camilleri, M.A. (2018). Theoretical insights on integrated reporting: The inclusion of non-financial capitals in corporate disclosures. *Corporate Communications: An International Journal*, 4(23), 567-581.

Chatterji, A.K., Durand, R., Levine, D.I. & Touboul, S. (2016). Do ratings of firms converge? Implications for managers, investors and strategy researchers. *Strategic Management Journal*, 8(37), 1597-1614.

Chen, Y., Li, T., Zeng, Q., & Zhu, B. (2023). Effect of ESG performance on the cost of equity capital: Evidence from China. *International Review of Economics & Finance*, 83, 348-364.

Cho, C. H., Roberts, R. W., & Patten, D. M. (2010). The language of US corporate environmental disclosure. *Accounting, Organizations and Society*, 35(4), 431-443.

Cohen, L., Malloy, C. & Nguyen, Q. (2020). Lazy Prices. *The Journal of Finance*, 3(75), 1371-1415.

Colonnello, S., Curatola, G., & Gioffré, A. (2019). Pricing sin stocks: Ethical preference vs. risk aversion. *European Economic Review*, 118, 69-100.

Dhandhania, A. & O'Higgins, E. (2022). Can “sin industries” prove their legitimacy through CSR reporting? A study of UK tobacco and gambling companies. *Accounting, Auditing & Accountability Journal*, 35(4), 1009-1034.

Dyer, T., Lang, M., & Stice-Lawrence, L. (2017). The evolution of 10-K textual disclosure: Evidence from Latent Dirichlet Allocation. *Journal of Accounting and Economics*, 64(2–3), 221-245.

Fabozzi, F. J., Ma, K. C., & Oliphant, B.J. (2008). Sin stock returns. *Journal of Portfolio Management*, 35(1), 82-94.

Fama, E. (1991). Efficient Capital Markets: II. *The Journal of Finance*, 46(5), 1575–1617.

Frattini, A., Bianchini, I., Garzonio, A., & Mercuri, L. (2022). Financial technical indicator and algorithmic trading strategy based on machine learning and alternative data. *Risks*, 10(12), 225.

Gatti, L., Seele, P., & Rademacher, L. (2019). Grey zone in – greenwash out: A review of greenwashing research and implications for the voluntary-mandatory transition of CSR. *International Journal of Corporate Social Responsibility*, 4(1), 1-15.

Ghouma, H. and Hewitt, C. (2019). Lobbying expenditures and sin stock market performance. *Research in International Business and Finance*, 49, 176-190.

El Ghoul, S., Guedhami, O., Kwok, C. C. Y., & Mishra, D. R. (2011). Does corporate social responsibility affect the cost of capital? *Journal of Banking & Finance*, 35(9), 2388-2406.

Gibson R., Krueger P., & Schmidt P. S. (2021). ESG rating disagreement and stock returns. *Finance Analysis Journal*, 4*(*77), 104–127.

Grindsted, T. S. (2021). Algorithmic finance: Algorithmic trading across speculative time-spaces. *Annals of the American Association of Geographers*, 5(112), 1390-1402.

Gu, A. Y. (2004). Increasing market efficiency: Evidence from the NASDAQ. *American Business Review*, 22(2), 20-25.

Hanley, K. W., & Hoberg, G. (2010). The information content of IPO prospectuses. *The Review of Financial Studies*, 23(7), 2821-2864.

Henriksen, L. (2012). Comprehensive tobacco marketing restrictions: promotion, packaging, price and place. *Tobacco Control*, 21(2), 147-153.

Huang, X., Teoh, S. H., & Zhang, Y. (2014). Tone management. *The Accounting Review*, 89(3), 1083–1113.

Horn, M. (2023). The influence of ESG ratings on idiosyncratic stock risk: The unrated, the good, the bad, and the sinners. *Schmalenbach Journal of Business Research*, Feb. 23, 2023, 1-28.

Jones, M. J. & Shoemaker, P. A. (1994). Accounting narratives: A review of empirical studies of content and readability. *Journal of Accounting Literature*, 13, 142-184.

Kapoor, S. & Prosad, J. (2017). Behavioural finance: A review. *Procedia Computer Science*, 5(122), 50-54.

Kacperczyk, M. T., & Hong, H. G. (2006). The Price of Sin: The Effects of Social Norms on Markets. *Sauder School of Business Working Paper*.

Khurana, D., Koli, A., Khatter, K., & Singh, S. (2023). Natural language processing: state of the art, current trends and challenges. *Multimedia Tools and Applications*, 82(3), 3713–3744.

Kim, I. & Venkatachalam, M. (2011). Are sin stocks paying the price for accounting sins? *Journal of Accounting, Auditing and Finance*, 26(2), 415-442.

Johri, P., Khatri, S.K., Al-Taani, A.T., Sabharwal, M., Suvanov, S., Kumar, A. (2021). Natural language processing: History, evolution, application, and future work. *Proceedings of 3rd International Conference on Computing Informatics and Networks*.

Li, F. (2008). Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics*, 45(2-3), 221-247.

Li, F. (2010). Textual analysis of corporate disclosures: A survey of the literature. *Journal of Accounting Literature*, 29, 143-165.

Lo, K., Ramos, F., & Rogo, R. (2017). Earnings management and annual report readability. *Journal of Accounting and Economics*, 63(1), 1-25.

Lopez de Silanes, F., McCahery, J. A., & Pudschedl, P. C. (2020). ESG performance and disclosure: A cross country analysis. *Singapore Journal of Legal Studies*, 2020, 217–241.

Malaquias, R. F. & Júnior, D. M. B. (2021). Positive tone in management reports and volatility of stock returns. *Global Business Review*

Malkiel, B. (2003). The efficient market hypothesis and its critics. *Journal of Economic Perspectives*, 17(1), 59-82.

Paradis, G. & Schiehll, E. (2021). ESG outcasts: Study of the ESG performance of sin stocks. *Sustainability*, *13*(17), 9556.

Pennebaker, J. W. & King, L. A. (1999). Linguistic styles: Language use as an individual difference. *Journal of Personality and Social Psychology,* 77(6), 1296–1312.

Puaschunder, J. M. (2016). On the emergence, current state, and future perspectives of socially responsible investment (SRI). *Consilience: The Journal of Sustainable Development*, 16(1), 38- 63.

Sadique, S., In, F., & Veeraraghavan, M. (2008). The impact of spin and tone on stock returns and volatility: Evidence from firm-issued earnings announcements and the related press coverage. *Working Paper.*

Tan, H. T., Ying Wang, E. and Zhou, B. (2014). When the use of positive language backfires: The joint effect of tone, readability, and investor sophistication on earnings judgments. *Journal of Accounting Research*, 52(1), 273-302.

Vanhamme, J. & Grobben, B. (2009). “Too good to be true!” The effectiveness of CSR history in countering negative publicity. *Journal of Business Ethics*, 85 (Supplement 2), 273-283.

Vargas, M. R., de Lima, B. S. L. P., & Evsukoff, A. G. (2017). Deep learning for stock market prediction from financial news articles. *2017 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA)*.

You, H. & Zhang, X. (2009). Financial reporting complexity and investor underreaction to 10-K information. *Review of Accounting Studies*, 14, 559–586.