ESG Disclosures in 10-K Filings: Sectoral Patterns and Stock Market Effects

1 Introduction

In the evolving landscape of corporate responsibility, the integration of Environmental, Social, and Governance (ESG) considerations into business practices has garnered increasing attention from investors, regulators, and stakeholders alike. This shift reflects a broader understanding that sustainable practices are not only ethically imperative but can also influence financial performance. In the remainder of this section I elaborate on the existing literature that induces this research. In section 2 I outline the methodology I undertook in the analysis followed by a brief description of the data forming the corpus in section 3. Section 4 will present my findings and section 5 will conclude with a discussion of the results and limitations, offering future areas of research.

The motivation for examining the relationship between ESG disclosures and stock performance is well-founded in the literature. Companies with robust stakeholder engagement and transparent Corporate Social Responsibility (CSR) reporting can reduce capital constraints, as improved transparency and internal control systems enhance compliance and reliability in reporting (Cheng, Ioannou, and Serafeim, 2014). Furthermore, CSR reporting is often regulation-driven, particularly in industries like utilities where regulations play a significant role in shaping corporate behavior (Bassen, Meyer, and Schlange, 2006). The assumption that regulatory pressures drive CSR activities is supported by findings that companies with high CSR performance exhibit lower regulatory risks, thus potentially reducing their cost of capital (Bassen, Meyer, and Schlange, 2006). Therefore, I hypothesize that firms with higher frequencies of ESG terms in their reports are perceived as lower risk, attracting more investment and possibly affecting their stock prices positively. This assumption is grounded in the theory that improved CSR performance, signaled through frequent ESG disclosures, can lead to a reduction in business risks associated with non-compliance and poor environmental and social practices. Such reductions in risk have been shown to lower the cost of equity and enhance shareholder value (El Ghoul et al., 2011).

In addition to lowering their perception of corporate risk, companies that perceive their social standing as potentially compromised have a direct financial incentive to communicate their engagement in practices and reforms that aim to enhance their public image (Lindblom, 1994). Thus, the adoption of ESG practices and the frequency of related disclosures in corporate filings could be used as a tool to 'greenwash' companies' reputations in an attempt to influence stakeholder perception and to boost their financial performance. This would be particularly for industries traditionally associated with high pollution levels as these have been historically neglected by norm constrained investors and are more susceptible to litigation (Hong and Kacperczyk, 2009). Moreover, existing studies that have attempted to glean insight on this topic comparing a variety of sectors have found negative effects of ESG themes in disclosures for high-risk sectors, calling for an investigation into that specific sectoral pattern (Ignatov, 2023). This paper delves into whether these high-pollution industries are escalating their discussions on ESG topics within annual 10-K reports and examines whether the ongoing patterns of ESG disclosure effects on their stock performance. I find that while adjusted stock prices are significantly influenced by ESG word counts in corporate filings, there is no effect on the cumulative abnormal returns. This confirms the existing literature that finds ambiguous results of ESG performance on stock returns (Gillan, Koch, and Starks, 2021).

2 Methodology

In order to perform frequency analysis of ESG term use in corporate disclosures I employ the dictionary used by Ignatov (2023) in his analysis of 10-K filings. He uses the domain-specific dictionary created by Baier, Berninger, and Kiesel (2020) who create an ESG word list specifically from 10-K reports and proxy statements. This is quite important because in order for dictionary methods to be successful the dictionary is ideally domain specific. Nevertheless, it is important to acknowledge that employing machine learning methods can generate more accurate and comprehensive feature spaces compared to those derived from dictionary-based approaches (Barberá et al., 2021).

A major assumption of dictionary methods is that the content of topics and features that represent a particular topic are assumed to be known a priori (Quinn et al., 2010). This means that the categories that shape analysis are determined prior to analysis, thus there are no new dimensions of latent concepts that are extracted from analysis. In addition, since the dictionary used was self-constructed from a corpus of 10-K filings, the dictionary is biased toward corpus words (Pollach, 2012), limiting the extent to which these findings could be generalized to other mediums.

Despite the drawbacks to dictionary-based methods they are useful to tabulate frequencies of ESG related words within a corpus. Utilizing the *dfm_lookup* function from the `quanteda` package, I conduct a temporal frequency analysis on several elements: the 13 ESG categories from the hierarchical dictionary, the 490 words within the ESG dictionary, and the target companies in the S&P 500 index. I choose companies from the utilities, materials, and energy sectors using the Global Industry Classification Standard (GICS) because utilities, materials, and energy sectors were three of the top four sectors with the highest greenhouse gas emissions between 2011 and 2017 (Guastella et al., 2022). I also include the industrials sector because it has increasingly become the target of regulatory bodies (Ramanathan et al., 2010).

Given that the primary focus of this paper is on the counts of ESG terms and categories within sectors and individual companies, I include analysis that controls for document length by proportionally weighting the document-term-matrix and analysis that focuses on the raw counts. This is done because documents with greater lengths are assumed to have more terms. Moreover, proportions facilitate measurement using a standard unit of analysis.

3 Data

To identify companies for analysis, I web-scraped the S&P 500 component stocks table from Wikipedia to obtain their Central Index Key (CIK). This key was used to target corporations listed in the S&P 500. I then compiled the corpus by parallelizing the extraction of 10-K annual reports from the SEC's EDGAR database, employed the `edgar` package in R, using the CIKs from the scraped table. Due to storage, computational, and temporal constraints, I focused on 10-K annual reports filed by publicly listed corporations in the S&P 500 index, specifically from the aforementioned GICS sectors, spanning from the start of 2016 to April 2024 in the first and fourth quarters of the fiscal year. Upon initial examination, it became apparent that not all companies were consistently part of the S&P 500 index throughout the specified date range. Therefore, to avoid over-representation in the corpus, I excluded companies that did not have at least one filing every year between 2016 and 2024. This approach yielded data for 124 corporations, each represented by nine observations corresponding to annual entries. While this step did remove some valuable information, the omission was performed after careful examination of the distribution of total filings per company which indicated a positive-tailed distribution, suggesting that the overwhelming majority of companies had 9 filings as can be seen in Figure 5 in Appendix A. This procedure induced a corpus of 1,116 documents.

4 Results

4.1 Frequency Analysis

Overall I find that the raw count of ESG words has substantially increased in the period of analysis as seen in Figure 1. It is important to note that many of the top 50 terms are words used to discuss remuneration (see Figure 6). This implies that despite ESG words increasing over time for high-polluting sectors, a lot of the increase may be due to the increasing use of governance terms. Indeed, examining the decomposition of ESG categories over time in Figure 2 highlights that about 50% of the annual filings

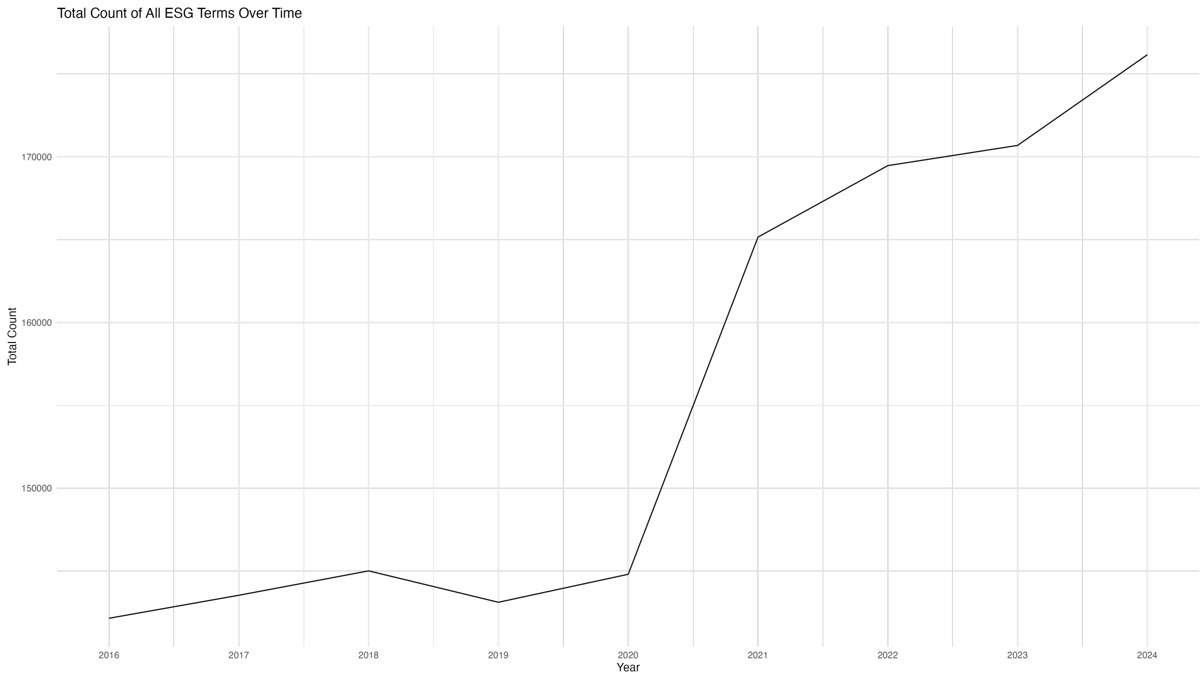

Figure 1: Raw Count of ESG Terms.

are concerned with corporate governance (once stopwords have been omitted). Thus, this decomposition suggests that companies in high-polluting industries are most likely not discussing environmental or climate strategies at great length (see the dominance of governance terms in FIGURE 7), although the share of words discussing climate change is slightly increasing the past three years. In order to examine which category has seen the greatest changes or fluctuations I calculate a year-over-year percentage change within each category as seen in FIGURE 3. It appears as though there are no persistent patterns for any of the categories, possibly due to the fact that filings reflect the dominant world narratives of the filing year. Many of the categories such as climate change and environmental management seem to have a spike in 2022. The pronounced spikes for "Human Rights" and "Public Health" may correlate with the strong resurgence of the Black Lives Matter movement and the onset of the COVID-19 pandemic. Thus, the spikes may be attributed to ongoing movements/shifts in the social status quo.

Finally, FIGURE 4 shows the proportions filings that are ESG terms by company grouped by sector. It seems that across all four sectors have experienced a slight increase in ESG terminology. The energy and materials sectors have seen the biggest increases, while utilities have seen the smallest change. This supports previous findings that found evidence in support of risky industries that minimize risk by engaging in ESG related

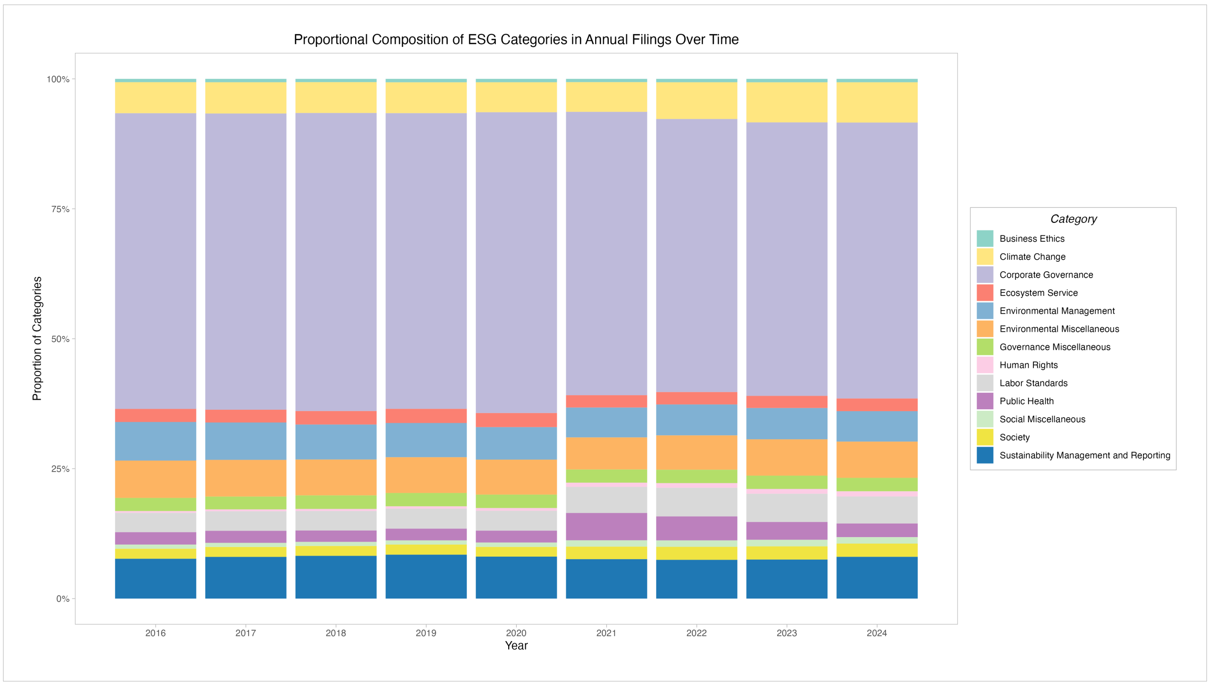

Figure 2: Decomposition of ESG categories.

initiatives (Jo and Na, 2012).

4.2 Regression Analysis

Leveraging the panel structure of my data, I run two separate fixed-effects regression. I merge financial fundamentals data for every firm using the `simfinapi` and then I also merge abnormal returns data using data from the Wharton Research Data Services (WRDS) US. Daily Event Study, designating each filing date as the date of the event. Model 1 in Table 1 is specified by cumulative abnormal returns on a company's stock. This specification allows for analysis of long-run effects of ESG word counts on stock performance while controlling for risk (Edmans, 2011). I control for market and firm conditions using the control variables in Table 1 that are a combination of previous studies performed by Ignatov (2023) and Krüger (2015). I find that the ESG word count has a positive but insignificant effect on cumulative abnormal returns, however, this finding should be interpreted merely as an association due to the relatively low R^2 indicating there may be omitted variable bias. Meanwhile the positive effects of ESG word count on the log of adjusted closing price are significant at the 1% level. This specification the model may be a lot better adept at explaining changes in the adjusted closing price of a

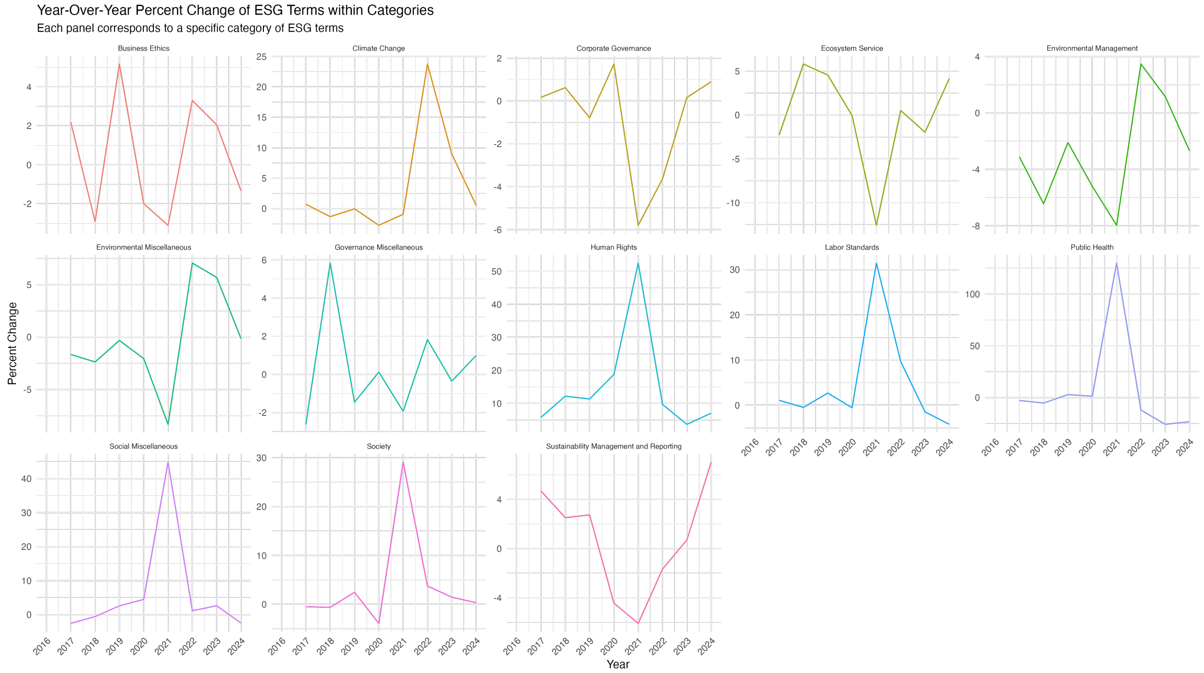

Figure 3: Year-over-year percentage change in category frequency.

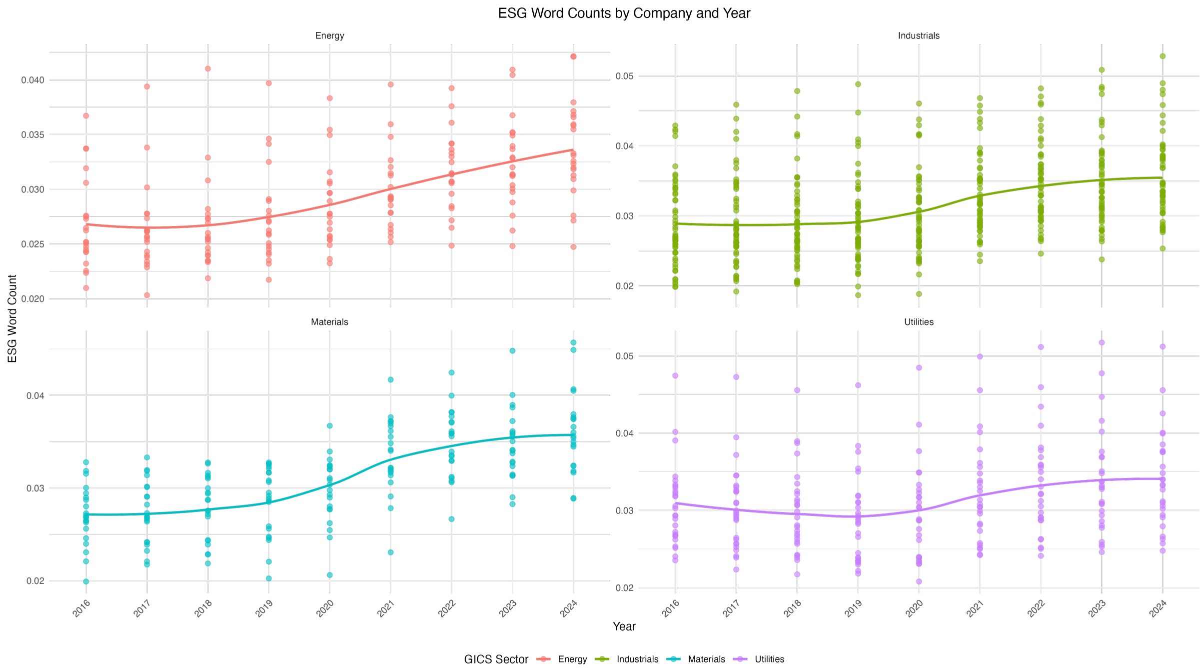

Figure 4: Time-series of ESG proportions by company and averaged by sector.

stock, as the R^2 is 0.73. The results from this model are in line with findings by Flammer (2013), Gillan, Koch, and Starks (2021), and Ignatov (2023) who find that earnings announcements with characterized by strong ESG performance are positively related to financial performance.

Table 1: Fixed Effects Model Results for CAR and Adjusted Closing Price

	Dependent variable:	
	CAR Model	Adjusted Closing Price Model
	(1)	(2)
ESG Word Count	2.307	5.466***
	(2.293)	(1.172)
Price to Book Value TTM	0.0002	0.0002**
	(0.0002)	(0.0001)
Altman Z-Score TTM	−0.003	0.021***
	(0.005)	(0.002)
EV/EBITDA TTM	0.00001	0.00001
	(0.00001)	(0.00001)
Book to Market Value TTM	0.154***	−0.056***
	(0.019)	(0.012)
Price to Earnings Ratio TTM	−0.00004	0.00003
	(0.00004)	(0.00003)
GICS Sector	−0.923**	−2.106***
	(0.363)	(0.191)
Dividend Yield TTM	−0.026	0.662***
	(0.023)	(0.012)
Log(Market Cap)	−0.00001*	0.00000
	(0.00000)	(0.00000)
Price to Free Cash Flow Quarterly	−0.080	1.251***
	(0.118)	(0.060)
Observations	636	3,048
R^2	0.230	0.730
Adjusted R^2	-0.254	0.697
Note:		*p<0.1; **p<0.05; ***p<0.01
		Standard errors in parentheses
		Significance levels: *p¡0.1; **p¡0.05; ***p¡0.01

5 Discussion

Conducting time-series frequency analysis I come to an obscure conclusion on whether ESG word counts trend with stock performance. The absence of a discernible pattern corroborates the observations by Capelle-Blancard and Petit (2019) who find that firm's filings are not as provocative as media articles, therefore other mediums of risk disclosure may have more of an effect on stock performance. This could be due to the stock market's incomplete valuation of intangibles, which may include ESG performance. My analysis does find that ESG sentiments as measured by frequencies of words within annual corporate 10-K filings is increasing over time. Given the narrow scope of this analysis, I forgo examination of the significance individual words possess. Another shortcoming of this exploratory research is the lack of validity check to the dictionary-based method. Future research exploring this aspect using a more robust method could provide valuable insights into the application and sentiment of ESG terminology within corporate 10-K filings. A word embedding model could capture more of the context in which ESG terms are used and it may be more representative of patterns within ESG word use in filings while being readily adaptive to new words and changes in terminology over time.

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Appendix A

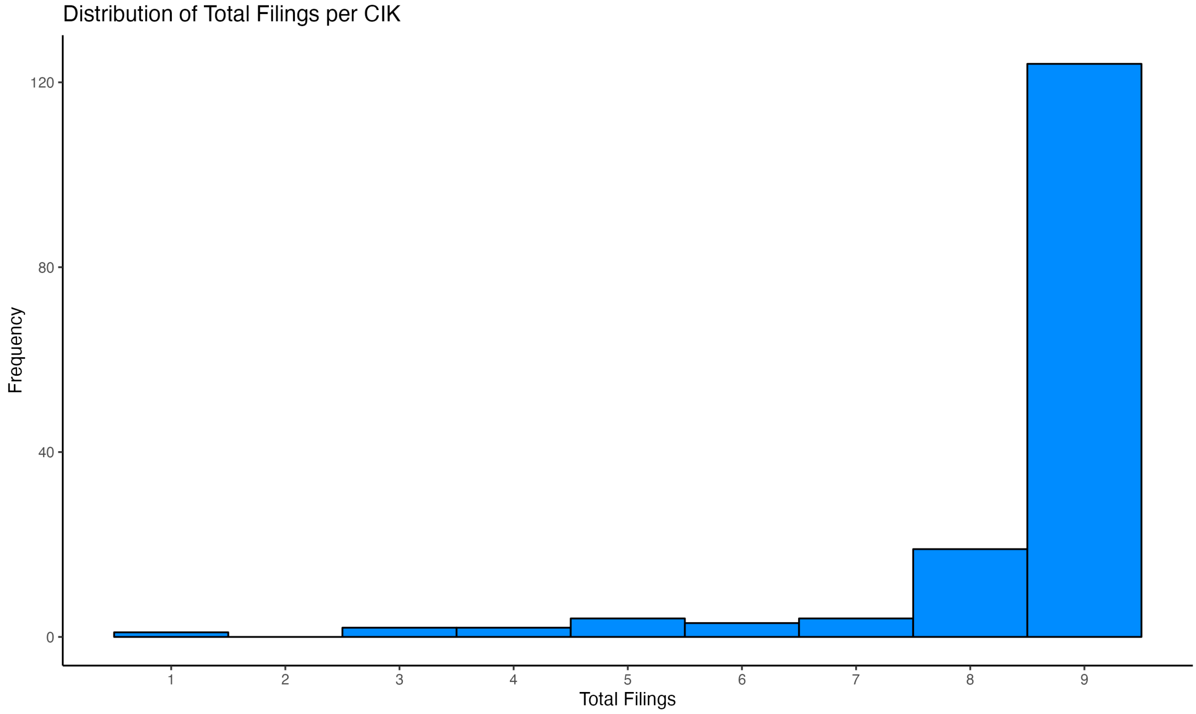

Figure 5: Histogram of total filings per company. (See discussion on page 4.)

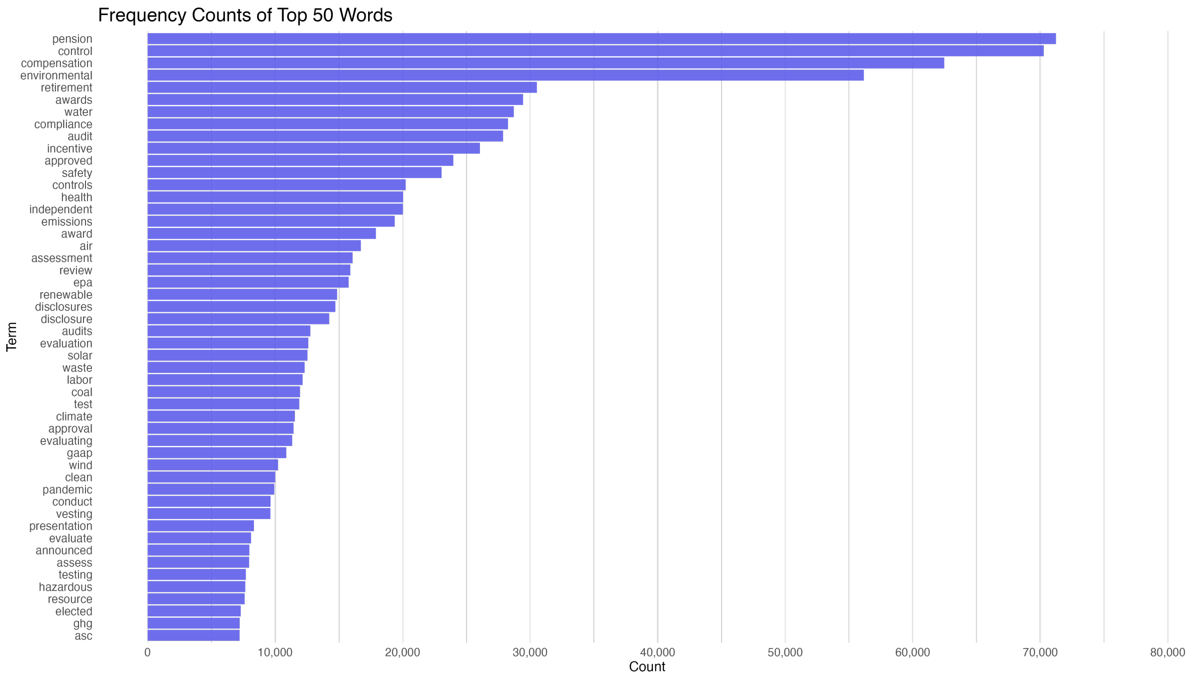

Figure 6: Top 50 ESG Terms. (See discussion on page 4.)

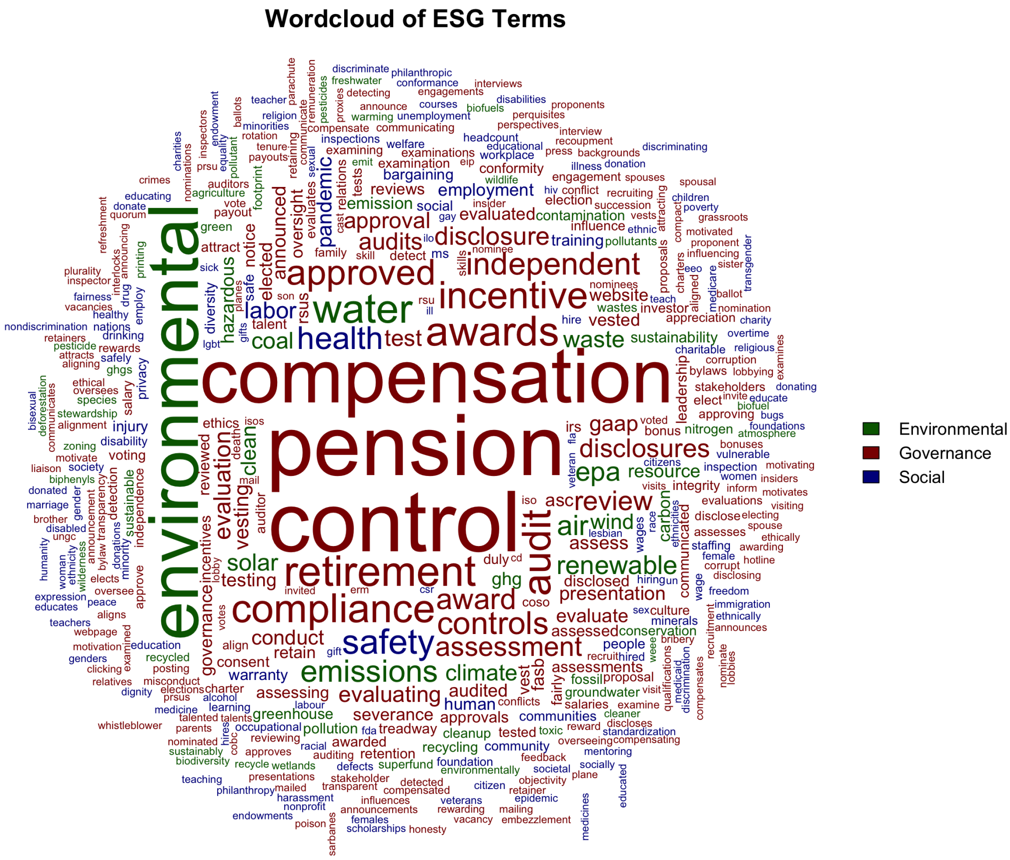

Figure 7: Wordcloud of ESG terms. (See discussion on page 5.)