FINANCIAL ANALYSTS' COVERAGE, FORECAST ACCURACY, AND CLIMATE CHANGE VULNERABILITY

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Abstract

The effects of climate change are real. The understanding of how these effects manifest in business operations is still nascent, but even more so, how they affect users of company information. This study sought to determine whether and how climate change vulnerability relates to an important business stakeholder, the financial analyst. We hypothesize that climate change vulnerabilities reduce both analysts' following and analysts' forecast accuracy. Using data from the Center for Research in Security Prices (CRSP), Compustat, Audit Analytics, Institutional Shareholder Services (ISS), and London Stock Exchange Group (LSEG), we construct a sample of 3,754 firm-year observations comprising 1,269 unique firms for the years 2019–2022. Our proxy for climate change vulnerability is the environmental, social, and governance (ESG) controversies score. We estimate cross-sectional regression models to test our hypotheses. We find support for our hypotheses. Also, we find that firms with high climate change vulnerability have significantly lower analyst coverage than those with low vulnerability. We also find that financial analyst forecasts are significantly less accurate for firms with higher vulnerability. However, this effect is only observable in industries classified as more exposed to the effects of climate change. We recognize the noisy nature of our proxy for vulnerability to climate change. Cognizant of this, we conduct further analysis to allay concerns of bias in our findings. We make important contributions to the existing literature by not only showing that ESG controversies score is an appropriate proxy for climate change vulnerability but also by adducing empirical evidence that climate change vulnerability affects how analysts react to and use company financial information. We discuss the significance and limitations of our results and make recommendations for further research.

Keywords: Financial Analysts, Forecast Accuracy, ESG, Climate Change Vulnerability, ESG Controversies

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1. INTRODUCTION

Currently, climate change may be the most talked about phenomenon that affects society globally (He et al., 2022; Panfilo & Krasodomska, 2022; Sobehart, 2021). Climate change has adversely affected nature and the availability of key resources that are used to drive the economy. Therefore, it is viewed as the most critical issue globally (Kalyani & Mondal, 2024). Furthermore, the adverse effects of climate change are on the increase due to the overuse of key resources such as water, wood, agricultural produce, and energy (Corvellec et al., 2021). Some of the nature-related issues that influence the availability of these resources are pollution, carbon emissions, soil erosion, and flooding, among others.

Consequently, climate change has affected the global economy (Gough, 2023; Huwei et al., 2023), and the effects are well documented (Huang et al., 2018). These effects continue to take place and are felt at all levels: international (Gough, 2023; Huwei et al., 2023), national (Kantur & Ozcan, 2022), industry and firm (Han et al., 2023; Hoang, 2022; Sautner et al., 2023; Hadzi-Velkova et al., 2022), and individual (Egan et al., 2022). Similarly, the accompanying risks are also felt at all these levels (Hadzi-Velkova et al., 2022).

To attenuate these risks, both governmental and non-governmental players have developed strategies for climate change adaptation and resilience building. These strategies create value for investors (Greer et al., 2022) and hence improve the economy. This has resulted in certain investor behavior. For example, Zilja et al. (2022) document that multinational enterprises incorporate climate change-related factors in making their foreign subsidiary investments. Relatedly, institutional investors have been financing climate change action (Girón & Ivanova, 2023). Overall, climate change is a sophisticated phenomenon with multi-level challenges (Wade & Griffiths, 2022) to the entire economy and stakeholders.

At the company level, climate change is a risk that affects not only firm performance but also firm value. Research is indeterminate on how investors view climate change risks. Some investors are keen on climate change investments and associate them with long-term value. However, others see such investments as expropriation of their wealth by the executives. These effects are enhanced in the corporate milieu by the overuse of resources. Corvellec et al. (2021) suggest the theory of resourcification to explain how this works. It is believed that these effects will be more apparent in the future but some of the environmental and policy impacts are already manifest.

While vast research has been conducted on climate change risks on the economy, not much has been done about climate change as a financial risk and how it affects the users of corporate information. Furthermore, Whieldon et al. (2023) note that most companies are yet to understand the business risks associated with nature leading to growing attention from firms, investors, and governments. Related to these, companies are now focusing on how to leverage climate change data availability to measure the nature of impact and dependency (Mankirar, 2023) and assess credit risk using climate credit analytics (S&P Global Market Intelligence, 2021). Our study contributes to these diverse understandings.

We seek to answer two questions:

RQ1: Whether climate change risks (vulnerabilities) as measured by environmental, social and governance (ESG) controversies influence financial analyst following?

RQ2: Whether climate change risks affect forecast accuracy?

These are important questions because the effects of climate change on business operations and on the use of corporate information are still not well understood or even agreed upon. We have multiple motivations for this study. First, the availability of data on ESG controversies allows us an opportunity to speak to climate change vulnerabilities. Second, there is a dearth of empirical evidence on climate change risks and investor decisions. Third, we find disagreements among researchers on the few studies that have been carried out relating to climate change risks.

Extant literature documents that some institutional investors do not believe that stock valuations incorporate climate-related risks (Krueger et al., 2020). For the accounting profession, a concern has been how to make high-quality disclosures on climate change and related company activities (Simnett et al., 2009). Hence, as the effects of climate change continue to be felt, adapted to, and mitigated all over the world, a better understanding of how they shape the business environment is important (Sobehart, 2021). This calls for more research in this area. We contribute to this research from the financial analyst perspective.

Our study also contributes to the literature in several other ways. First, proponents of the stakeholder theory argue that firms do not only focus on the interests of the shareholders but also a battery of other stakeholders. Hence, investors aligned with this theory understand that firms can create value not only by mobilizing internal resources but also by taking a keen interest in what happens to the environment and society. While the ESG scores can provide information about this, financial analysts are able to see through simplistic image management activities. Our study sheds light on how these sophisticated users of financial information perceive the ESG performance, and the related vulnerabilities. Second, while previous studies (Aydoğmuş et al., 2022) have shown that ESG performance is significantly and positively associated with firm value, no study has examined how financial analysts respond to environmental risks and to what extent they incorporate such risks into their forecasts. Third, as Grove et al. (2024) point out, it is still not known how ESG reporting delivers value to stakeholders. A contemporaneous systematic literature review by Kalyani and Mondal (2024) does not find any research evidence on this aspect of ESG reporting. Our study fills this gap in the literature.

In this study, we focus on how climate change vulnerabilities affect financial analysts' coverage and accuracy of forecasts. As sophisticated users and providers of financial information, their forecasts would ex ante be expected to have built-in climate change risks, as predicted by the efficient market hypothesis. This is important given that investors are increasingly interested in the risks associated with non-financial factors such as the environment (Aydoğmuş et al., 2022).

We seek to answer the question as to whether financial analysts consider climate change vulnerabilities in their forecasts. Specifically, we seek to determine whether companies with high vulnerabilities are less covered and whether their forecasts are less accurate compared to companies with low vulnerabilities. Furthermore, climate change vulnerabilities affect companies differently depending on the industry and other factors such as foreign markets where they operate and source their raw materials. Therefore, we also seek to determine whether there are industry differences in financial analyst coverage and forecast accuracy. While most studies examine climate change risks from the perspective of greenhouse gas emissions (Huang et al., 2018) and the related disclosures, our study is different. Our study is closely related to contemporaneous research by Sautner et al. (2023), in which the authors examine firm-level climate change exposure. They use earnings call data from financial analysts to construct climate change exposure measures. While their exposure measures focus on the attention paid to climate change exposure at a point in time, our variable is a measure of fundamental exposure, which, therefore, includes potential future effects. We use a comprehensive vulnerability index that measures climate change risks by incorporating many variables and indicators aside from greenhouse gas emissions.

The paper is organized as follows. In the next Section 2, we review the literature and develop our hypotheses. In Section 3, we present our research methodology. We present our results in Section 4 and discuss our findings in Section 5. In Section 6, we conclude, note limitations to our research design, and suggest areas for further research.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Research shows that most of the world's big firms are highly dependent on nature for their operations (Whieldon et al., 2023). Furthermore, about half of these companies obtain at least one of their assets from a key biodiversity area location, which is likely to be associated with future risks related to overexploitation. This reality exposes many companies to serious challenges and justifies the need for their involvement in the preservation of nature. Some of these challenges could include sustainability of returns and reliability of performance forecasts, among others. In addition, other constituents who are affected by this uncertainty include financial analysts, who must use past, present, and future data to make performance predictions for investors and company executives. Other users, such as lenders, also make use of these forecasts in estimating corporate risks, credit rating, and loan pricing. Whieldon et al. (2023) note that though most companies are yet to understand the business risks associated with nature, there is growing attention from firms, investors, and governments on this matter. Notwithstanding, identifying and managing nature-related dependencies can help companies deal with the accompanying legal, regulatory, reputational, and market risks.

Consequently, firm operations are likely to be affected by climate change. The effects vary depending on the products and services the firm provides. By the same extension, the negative effects of climate change impact diverse constituencies to different extents. Companies that rely more on resources that are highly vulnerable to the effects of climate change are more likely to be associated with sustainability issues and forecast difficulties.

Another way that companies must grapple with climate change effects is the adoption and compliance with upcoming climate policies (Cummings, 2022; He et al., 2020). Coupled with accompanying regulations, these have indicators that must be reported. For example, in Germany, the Federal Climate Change Act requires companies in industrial and service sectors to adjust their operational practices, while financial institutions must use new evaluation criteria (Ballesteros et al., 2023). Research by Hoang (2022) documents that the unpredictable nature of climate change policies influences corporate research and development (R&D) expenditures in a way that depends on the extent of greenhouse gas emissions. There are other ways that companies are affected indirectly. In the United States, for instance, climate change has been associated with increasing mortality (Deschenes, 2022). This increase, in turn, points to increased investment in health care systems and electricity costs to cope with the extreme temperatures that are consequences of climate change.

Climate change has also been shown to be associated with citizens' attitudes about environmental concerns (Egan et al., 2022). As Egan et al. (2022) contend, this has made Americans more aware and sensitive to environmental issues through ascendancy in public opinion due to incessant news and surveys. Alvarez (2012) adds that nowadays, it is not uncommon to find workers and consumers who prefer products and services from low greenhouse gas emitters. Furthermore, companies can also access new forms of capital that are attached to government incentives for the reduction of greenhouse gas emissions.

The greenhouse gas debate takes a different direction for high-energy-user industries. This is because 81% of global energy requirements still rely on carbon technologies, which are high emitters (Hale, 2022). The mooted alternative of electric energy substitutes does not make it any better for companies in developing countries with low mineral resources and larger carbon footprints, which rely on investors who have novel ESG requirements. Hale (2022) argues that the exclusion of funding for carbon fuel technology could result in capital misallocation.

Overall, climate change is affecting the social, geopolitical, and financial dynamics of contemporary society (Venturini, 2022). Kantur and Ozcan (2022) argue that the most meaningful way of having an effective policy on climate change mitigation is the decarbonization of company operations. Hence, companies must also be aware of how climate change influences their operations (Alvarez, 2012). Companies must find a balance between what risks to disclose and which not to (Griffin et al., 2017). This is due to the tension between the investor's demand for more disclosures on the one hand and the costs of disclosure on the other.

Climate change is now agreed as a monetary policy risk (Kantur & Ozcan, 2022) and company risk (Kanagaretnam et al., 2022). This company risk has been characterized as having two components (Venturini, 2022). First, there are physical risks. This relates to the adverse effects of climate change on company operations, society, and supply chains. Second, there are transitional risks that relate to greenhouse gas emissions. Companies that are heavy emitters of greenhouse gases have been shown to invest less in R&D (Hoang, 2022) due to climate change policy uncertainty. Results are the opposite for average companies. Policy uncertainty arises from the challenges that policymakers face in designing them to mitigate climate change effects on the economy (Kantur & Ozcan, 2022). Furthermore, capital market imperfections affect the costs of implementing these policies (Leimbach & Bauer, 2022).

At the firm level, certain climate change aspects have been shown to be significantly associated with firm risk. Citing evidence from the United Kingdom, Alsaifi et al. (2022) document that increasing voluntary carbon disclosure was negatively associated with not only firms' total risk but also their systematic and idiosyncratic risk. This relationship was more pronounced in carbon-intensive industries. However, these results are in contrast to those by Han et al. (2023), who find no significant association between voluntary disclosures and firm value[1]. Earlier studies adduce evidence that companies can attenuate capital markets valuation discounting by reporting their carbon emissions (Saka & Oshika, 2014).

Related to this is the observation that more investors are increasingly paying more attention to climate change in their decisions (Babcock et al., 2022). With this, it is expected that climate change disclosures on commitments are likely to be associated with market reactions (Babcock et al., 2022). Moreover, Ouazad and Kahn (2022) find that lenders are more likely to issue securitized mortgages after natural disasters in a bid to transfer climate risk.

Many researchers and organizations have indicated that the global economy will be adversely affected by climate change risks, especially greenhouse gas emissions. However, others (Gough, 2023) have shown theoretical and empirical evidence that this is not the case. This view shows that not all constituencies agree or are at least convinced that climate change is a risk, as claimed. Furthermore, there is no consensus as to how the climate change risks relate to stock returns (Venturini, 2022). Risks related to climate change have also been associated with firm performance and corporate social responsibility (CSR) activities (Ozkan et al., 2011).

Climate change risk is significantly and positively associated with physical capital but negatively associated with organizational capital (Kanagaretnam et al., 2022). Climate vulnerability differences among industries drive these results. Climate change also affects resource prices, including energy, among others (Kantur & Ozcan, 2022). Climate change risk is also associated with litigation risk (Macchi & van Zeben, 2021) under international investment law.

Consequent to the aforementioned, stakeholders demand and react to climate risk disclosures (Panfilo & Krasodomska, 2022). These reactions further depend on whether the disclosures are positive or negative and whether the company is in a climate-harmful industry. These disclosures are not yet standardized and are not easily compared across companies (Amran et al., 2014; Sullivan & Gouldson, 2012). Recently, researchers have developed approaches to assess the risks of company strategies that will be affected by climate change (Sobehart, 2021).

Risks related to climate change can be further categorized as either financial or non-financial. As financial risks, one would consider how they affect company returns and total risks (Krueger et al., 2020). There is also the argument that building climate change risks into the value chain can attenuate return risks. In support of this view, Serafeim and Yoon (2022) document positive market reaction to financial material ESG pronouncements. This suggests that investors understand climate change as a real financial risk. In a related study, Griffin et al. (2017) find that investors are not indifferent to greenhouse gas emission disclosures and that they are associated with changes in equity values. Similar results from developed economies have documented that increases in carbon emissions are negatively related to firm value (Han et al., 2023; Johnson et al., 2020). The effects of climate change risks on firm performance and the financing choices that executives make have also been examined. Huang et al.'s (2018) findings show that companies change their financing choices, including how much cash they hold, depending on their locations in relation to climate change risks. They further argue that inevitably, corporate managers must consider climate risks in their financial decisions given that not all climate risks can be insured against (Huang et al., 2018).

However, Babcock et al. (2022) find empirical evidence that not all climate change-related disclosures are associated with market reactions. Furthermore, Griffin et al. (2017) find that there is no consensus as to the import of these disclosures to investors. Due to climate change, Girón and Ivanova (2023) argue that global financing strategies are in a change mode, with institutional investors experiencing a field day due to the possible windfall profits associated with financing actions meant to achieve sustainable development goals. Other research findings by Krueger et al. (2020) show that institutional investors recognize climate change risks as a factor in portfolio returns. This research further indicates that some institutional investors do not believe that stock valuations incorporate climate-related risks (Krueger et al., 2020).

Several types of financial risks have been identified as related to climate change (Venturini, 2022). These are credit risks, underwriting risks, operational risks, and market risks. Furthermore, different assets would be impacted in diverse ways by climate change issues. For example, the market value of some assets (e.g., weather, real estate, biological assets) would be significantly affected by risks related to climate change. Further, physical risks have been shown to be driven by hazards, exposure, and vulnerability (Tankov & Tantet, 2019). These findings indicate that company vulnerabilities to climate change can significantly affect the firm value.

Climate change risks have also been characterized by examining how they affect the equity market (Venturini, 2022). Some of these studies have focused on market reaction to climate change disclosures. Studies have been conducted at both the firm level and the investor level. Hadzi-Velkova et al. (2022) mention that risks related to climate change are felt at all levels: macro, meso, and micro. At the macro level, governments

[1] These results are from Taiwan. Han et al. (2023) attribute this discrepancy to the carbon emissions regulatory framework in Taiwan compared to those in developed economies.

have to make price adjustments for energy costs; central banks are increasingly coming up with regulations related to climate change adaptation finance (Angeli et al., 2022). The Climate Risk Index is used to measure risks at this level (Kanagaretnam et al., 2022). At the meso level, certain industries bear more of the effects of climate change, especially those associated with high greenhouse gas emissions. At the micro level, companies have to decide how to adapt and mitigate both physical and transitional risks according to how their operations are affected. This is more so when issues of sustainability are considered. There are ESG company scores that are indicators of company-level vulnerabilities to climate change risks.

A major challenge associated with this risk is how to estimate the time horizon within which it would be manifest financially. This is partially because the risk is highly uncertain (Kanagaretnam et al., 2022) as to the time, nature, and magnitude. These are termed scientific uncertainty and socioeconomic uncertainty (Heal & Millner, 2014). Another reason for the uncertainty is that the tools for estimating these risks are nascent and dependent on many economic variables (Kantur & Ozcan, 2022). All the same, investors keen on the financial risks associated with climate change have been found to engage companies in diverse dimensions (Krueger et al., 2020). Research also shows that although climate change risks can affect the main players in the financial system in diverse ways, the risks are not readily identified (Málits et al., 2022; Milkau, 2022). Approaches to quantify these risks have been made suggested as in Sobehart (2021).

Literature has documented that financial analysts are sophisticated users of financial information. They are critical players in the firm's information environment and the provision of predicted performance (Francis et al., 2019). The role of financial analysts in the corporate information environment and the attendant effect on firm value have been vastly documented in extant literature (Jo & Harjoto, 2014). Financial analysts have a monitoring role (Chung & Jo, 1996; Yu, 2008) and an informational role (Berk & DeMarzo, 2011; Qian et al., 2019) and are, therefore, quintessential stakeholders of the financial markets (Qian et al., 2019) who make evaluations and recommendations for the companies they cover.

Financial analysts are known to prefer companies that have certain characteristics. For example, literature finds that financial analysts prefer to follow companies that have more high-quality disclosures (Lang & Lundholm, 1996), high-quality corporate governance (Healy & Palepu, 2001), low cost of information acquisition due to their better information environment (Bhushan, 1989; Bushman et al., 2005), and that provide voluntary CSR disclosures (Hong & Kacperczyk, 2009). Financial analysts also fuel investor interest and firm liquidity (Anantharaman & Zhang, 2011). These characteristics are closely related to ESG reporting, which is a contemporary issue in corporate governance and financial reporting. Companies that are more affected by climate change have highly uncertain disclosures (Heal & Millner, 2014; Kanagaretnam et al., 2022) and hence, excessive cost of information acquisition.

Given that integrating climate risks into investment is still a challenging task (Krueger et al., 2020), one would expect that financial analysts avoid firms that are associated with higher climate change risks for two reasons: to avoid the prohibitive cost of forecasting and to avoid the possible inaccuracies in forecasting. In addition, factors that affect company operations are known to influence financial analysts' understanding and forecast earnings (Francis et al., 2019). To this extent, climate change vulnerabilities can be expected to affect financial analyst forecasts. Analyst forecast accuracy is important as it determines the value of the information analysts provide to investors for investment decisions (Francis et al., 2019). Extant literature documents declining forecast accuracy with diminishing earnings predictability (Lim, 2001). From the preceding, we state our first hypothesis.

H1: Companies with higher climate change risk have fewer financial analysts compared to those with lower risks.

ESG score refers to non-financial performance indicators used to assess the sustainability and ethical effect of corporate investments (Clerc, 2021). The environmental indicators in ESG relate to climate change (Clerc, 2021). ESG practices can affect auditor risk assessment and audit fees for their clients (Burke et al., 2019), including auditor resignations. Auditor resignation has a signaling effect and is associated with a negative market reaction.

Mounting interest in the financial effects of climate change has been noted (Bouchet et al., 2022). As Bouchet et al. (2022) document, different stakeholders have differing perceptions of climate change risks related to the financial system. These varied perceptions create impediments to consensus in vulnerability, valuation, and risk assessment. Borghei (2021) identifies carbon disclosures and climate-related risk disclosures as two areas affected by these differences in perception. Furthermore, Panfilo and Krasodomska (2022) find that cultural and normative factors significantly influence the quality of climate change disclosures.

In a related study, though not directly, Jo and Harjoto (2014) find empirical evidence to support increasing analyst coverage both at the level and changing perspectives with increasing CSR. Jo and Harjoto also find interesting results that financial analysts exert indirect social pressure on firms that may engage in socially and environmentally irresponsible activities. These results are significant for this study because CSR, just like climate change, provides important non-financial information for investors. Moreover, CSR is a manifestation of the executive commitment to improve corporate governance (Jo & Harjoto, 2014).

As argued by Jo and Harjoto (2014) for the case of CSR, it is plausible that some investors do not associate their returns with climate change effects while others do. Consequently, motivated by the overinvestment hypothesis, the former group would view any investments in climate change-related projects and activities as a method of expropriation for reputational rewards on the part of executives. However, the latter group would perceive such investment as beneficial for the sustainability of their returns. Some investors in this latter group may be proponents of the conflict-resolution hypothesis; investments in such projects help reduce the conflict of interest among stakeholders.

Financial analysts are known to exert short-term pressure on company executives who may have incentives to diminish investments in certain activities. Qian et al. (2019) document evidence of decreasing investments in socially responsible activities in response to financial analyst pressure. Moreover, He and Tian (2013) find that executives are willing to forego long-term and economically viable investments as they acquiesce to this pressure to meet short-term targets. Surveys (Graham et al., 2005; Barton et al., 2016) show that executives would be willing to cut certain spending to meet financial analysts' earnings targets.

A decrease in financial analysts' coverage increases information asymmetry between executives and investors and may be associated with an increasing risk of opportunistic behavior (Qian et al., 2019). To avert this perception, firm executives may engage in more disclosures, including ESG reporting. The quality of analysts and their market reputation is dependent on their experience and past forecast accuracy (Qian et al., 2019). Forecast accuracy is viewed as an indicator of the credibility of their recommendations. Moreover, forecast accuracy has been applied in prior literature as a measure of analyst quality and turnover (Wu & Zang, 2009). Hence, higher forecast accuracy would be associated with more pressure on firm executives. The other perspective on the issue of analyst following and forecast accuracy is that greater forecast consensus is associated with increased coverage (Graham et al., 2005). Greater consensus implies greater forecast accuracy. Climate change vulnerability differs by industry (Huang et al., 2018). Therefore, some industries are not exposed to climate change risks as high as others. Similarly, some industries rely more on natural resources that are subject to climate change effects than others. We contend that financial analysts' following behavior may also be characterized by industry conditional on climate change vulnerability. Thus, we state our second hypothesis as follows.

H2: Companies with higher climate change risks receive less accurate financial analyst forecasts than those with lower risks.

3. RESEARCH METHODOLOGY

3.1. Data sources

We obtain data from public sources, including Compustat (company financial data), Institutional Brokers' Estimate System (IBES, analyst following and earnings forecasts data), Audit Analytics (for auditor and internal control weaknesses data), Center for Research in Security Prices (CRSP) for the stock price and returns data, Institutional Shareholder Services (ISS) for corporate governance data, and Refinitiv ESG, London Stock Exchange Group (LSEG) company scores for climate change data.

3.2. Research design

We use a modified Irani and Karamanou (2003) research design and estimate the following cross-sectional regression model (Model 1) to test *H1* and *H2*.

$$\begin{aligned}ANFOL_{i,t} = \alpha + \beta_1 VUL_i + \beta_2 ANFOL_{i,t-1} + \beta_3 TA_{i,t-1} + \beta_4 EPS_{i,t-1} + \beta_5 EPSCH_{i,t-1} + \beta_6 SALCH_{i,t-1} + \beta_7 AR_{i,t-1} \\ + \beta_8 EPSVOL_{i,t-1} + \beta_9 RETVAR_{i,t-1} + \mu_i \sum_{2}^{n} IND_i + \delta \sum_{2}^{3} YR + \varepsilon_i\end{aligned} \tag{1}$$

The dependent variable is $ANFOL_{i,t}$ (total number of analysts following firm *i* over the year *t*), and our variable of interest is $VUL_{i,t}$, company climate change vulnerability index. All other variables are defined in Appendix.

In this model, the variable of interest is *VUL* and a negative β_1 is interpreted to mean that firms with high vulnerability to climate change have declining financial analyst coverage in support of *H1*.

To test *H2*, we adopt a modified cross-section regression model (Model 2) based on Mburu and Tang (2018).

$$\begin{aligned}ACCURACY = \alpha + \beta_1 VUL + \beta_2 CEODUALITY + \beta_3 LOSS + \beta_4 MKV + \beta_5 LEV + \beta_6 ANFOL + \beta_7 RDV + \beta_8 BIND \\ + \beta_9 BDSIZE + \beta_{10} DISP + \beta_{11} EPSVOL + \beta_{12} BIG6 + \beta_{13} ICMW + IND + YEAR + \varepsilon\end{aligned} \tag{2}$$

Our main variable of interest in Model 2 is forecast accuracy (*ACCURACY*), which is defined as consistent with prior research by Lang and Lundholm (1996) and Byard et al. (2006).

$$ACCURACY = \frac{|Forecast\ EPS - Actual\ EPS|}{Stock\ price} \tag{3}$$

Accurate forecasts have lower forecast error (meaning the numerator is close to zero). Hence, the lower the variable *ACCURACY*, the higher the forecast accuracy. A negative β_1 is consistent with financial analyst forecast accuracy declining for firms with high vulnerability to climate change in support of *H2*. The other variables in the model are defined as indicated in Appendix.

3.3. Sample construction

We start constructing our sample from the IBES universe for the years 2014–2022. We remove all firms that do not have sufficient data to compute the required forecast and actual earnings per share variables. We then merge these data with company financial data (from Compustat), removing firms that have missing data. We further merge with auditor data (from Audit Analytics), corporate governance data (from ISS), stock price data (from CRSP), and ESG data (from LSEG).

We limit our sample to 2019–2022 because the ESG dataset is available only from 2019. To avoid further data loss from our final sample, we set any missing values to zero. Our final sample consists of 3,754 firm-year observations comprising 1,269 unique firms from 67 industries (by 2-digit Standard Industry Classification [SIC] code) and spanning all the 48 Fama and French industry classifications. We summarize the sample construction in Table 1 below.

Table 1. Sample construction summary

Description	*Total observations*
IBES universe 2014–2022	24,019,411
Observations without CUSIP identifier, with duplicates, and with other stock categories besides common stocks	(23,991,899)
Observations with required actual and forecast EPS data	27,512
Observations with missing data from CRSP, Compustat, audit analytics, ISS, and LSEG	(23,758)
Final sample (1,269 unique firms)	3,754

3.4. Analysis

We use SAS software for all our analyses. We compute descriptive statistics of our main variables. To better understand our data and make a preliminary assessment of our hypotheses, we conduct a univariate analysis comprised of correlation and covariance and a test of differences (means and medians). We estimate cross-sectional multiple regression models to test our hypotheses. For *H1*, we estimate Model 1, and for *H2*, we estimate Model 2.

3.5. Sample distribution

Our sample comprises 3,754 observations distributed over four years (2019–2022). These firm-year observations are from 67 industries (by 2-digit SIC code) and the 48 Fama and French industry classifications. In Table 2, we show the distribution of the observations according to industry.

The distribution is similar over the four years and across industries. Firms in the Fama and French industry classifications 33 (Business services), 34 (Personal services), and 35 (Computers) have the highest percentage in any given year at between 8–9%. Altogether, 17 industries (25%) comprise about 70% of the observations both in total and in the different years.

We also classify our sample observations according to climate change exposure, as per Sautner et al. (2023) (who classify the following 2-digit SIC code industries comprising our sample as more exposed to climate change effects: 01, 02, 07,10, 12, 13, 14, 20, 21, 37, 44, 45, 46, 47, 49, and 50), and the S&P Index. We show this distribution in Table 3.

Table 2. Sample distribution by industry

2-digit SIC code	*Total observations*	*Fama and French code*	*Total (%)*	*Year 2019 (%)*	*Year 2020 (%)*	*Year 2021 (%)*	*Year 2022 (%)*
73	313	33, 34, 35	8	8	8	9	9
60	285	44	8	8	8	7	7
28	265	9, 13, 14	7	6	7	8	8
38	231	9, 12, 36, 37	6	6	7	6	5
36	224	5, 6, 9, 12, 22, 23, 35, 36	6	6	6	6	6
35	209	21, 23, 35	6	5	6	6	5
67	186	47	5	4	5	5	6
49	177	31, 48	5	5	5	5	4
37	170	5, 6, 9, 23, 24, 25, 26	5	5	4	5	5
63	110	45	3	3	3	3	2
20	99	1, 2, 3, 4, 9	3	3	3	2	3
34	80	17, 20, 26, 39	2	2	2	2	2
50	79	41	2	2	2	2	2
13	70	30	2	2	2	2	2
33	63	19	2	2	2	1	2
58	62	43	2	1	2	2	2
56	60	42	2	2	2	1	2
Others (51)	1071	Others	29	30	28	27	29
Total	3754		100	100	100	100	100

Note: The SIC codes and the Fama and French industry codes are not mutually exclusive because Fama and French classifications are based on the 4-digit SIC code. Hence some SIC codes appear in multiple Fama and French classifications.

Table 3. Sample distribution by years, climate change exposure and S&P Index

Year	*Firm-year observations*	*Climate change exposure*		*S&P Index classification*			
		High	*Low*	*500*	*400*	*600*	*Unclassified*
2019	983 (26.2%)	192	791	280	205	247	251
2020	902 (24.0%)	175	727	264	173	235	230
2021	925 (24.6%)	178	747	270	181	208	266
2022	944 (25.2%)	179	765	277	183	236	248
Total	3754 (100%)	724 (19%)	3030 (81%)	1091 (29.1%)	742 (19.8%)	926 (24.7%)	995 (26.5%)

Overall, we find that our sample observations are well distributed across years, industry, and in size as per the S&P Index. We do not anticipate any bias due to clustering or self-selection. However, we do find that only about 10% of our sample observations relate to firms in industries deemed to be more exposed to climate change effects. Whatever the reason for this observation, this distribution would bias our results against finding support for our hypotheses. This is because our study focuses more on the firms with high exposure than those with low exposure. Reporting significant results with this low proportion of observations would add credibility to our findings.

4. RESULTS

We now present our results for the study. We start by providing the descriptive statistics that characterize our sample firms. We then proceed to univariate analysis incorporating correlation analysis, covariance analysis, and differences in means and medians. We end the section by presenting the results for multiple regression estimations.

4.1. Descriptive statistics

The descriptive statistics show that a few variables may have outliers (*ACCURACY*, *EPSFX*$_{t-1}$, *EPSCH*$_{t-1}$, *DISP*, and *EPSVOL*$_{t-1}$). This is because the standard deviation for these variables is much larger than the mean; the maximum values are also extremely large compared to the mean values. To allay concerns arising from this possibility, we winsorize these variables at 5% and 95% in our additional analysis. Our results are quantitatively similar to those with the unwinsorized variables. We present our sample descriptive statistics in Table 4.

Table 4. Descriptive statistics

Variable	N	P5	Min	Mean	P50	Max	P95	STD
ACCURACY	3754	0.000	0.000	0.777	0.003	1300.990	0.275	22.067
VUL	3754	0.194	0.007	0.892	1.000	1.000	1.000	0.248
ESGSCORE	3754	0.198	0.036	0.478	0.471	0.950	0.771	0.178
LOSS	3754	0.000	0.000	0.188	0.000	1.000	1.000	0.391
MKV	3754	0.083	0.000	1.557	0.953	22.846	5.275	1.950
LEV	3754	0.010	0.000	0.278	0.271	2.084	0.624	0.210
ANFOL	3754	1.099	0.693	2.384	2.398	4.220	3.466	0.725
RDV	3754	0.000	0.000	0.032	0.000	0.926	0.233	0.088
CEODUALITY	3754	0.000	0.000	0.037	0.000	1.000	0.000	0.190
BIND	3754	0.000	0.000	0.006	0.000	0.923	0.000	0.067
BDSIZE	3754	0.000	0.000	1.660	2.197	3.135	2.565	1.014
DISP	3754	0.000	0.000	0.331	0.000	242.312	0.053	5.672
EPSAVOL	643	0.000	0.000	0.000	0.000	0.000	0.000	0.000
BIG6	3754	0.000	0.000	0.758	1.000	1.000	1.000	0.428
ICMW	3754	0.000	0.000	0.058	0.000	1.000	1.000	0.234
$ANFOL_{T-1}$	3754	1.099	0.000	2.362	2.398	4.220	3.466	0.763
TA_{t-1}	3754	5.636	-0.648	8.358	8.280	15.198	11.191	1.731
$EPSFX_{t-1}$	3754	-1.850	-998.260	2.623	2.060	140.560	10.280	17.818
$EPSCH_{t-1}$	3754	-0.101	-1208.830	0.017	0.004	692.533	0.170	24.752
$SALCH_{t-1}$	3754	-0.189	-2.366	0.105	0.058	18.715	0.473	0.495
AR_{t-1}	3754	-0.504	-1.227	0.011	-0.045	13.962	0.639	0.498
$EPSVOL_{t-1}$	3754	0.003	0.000	0.223	0.023	238.709	0.173	4.795
$RETVAR_{t-1}$	3754	0.012	0.000	0.026	0.022	0.184	0.051	0.014

Note: All the variables are defined in Appendix.

4.2. Univariate analysis

We seek preliminary support for our hypotheses using correlation analysis, covariance analysis, and tests of differences in means and medians. We expect to find significant correlations and covariances between our main variables. In addition, we expect to find significant differences in means and medians for firms with high vulnerabilities compared to those with low vulnerabilities.

4.2.1. Correlation and covariance analysis

We present the correlation and covariance results for our dependent variables and the independent variables of interest in Tables 5a and 5b, respectively.

Table 5a. Pearson's correlation results

Variable	ANFOL	ACCURACY	ESGSCORE	VUL
ANFOL	1	-0.012 (0.4504)	0.467*** (< 0.0001)	-0.335*** (< 0.0001)
ACCURACY		1	-0.033** (0.0422)	0.0002 (0.9921)
EGSCORE			1	0.041** (0.0114)
VUL				1

*Note: ***, **, and * represent the level of significance at 1%, 5%, and 10%, respectively.*

Table 5b. Standardized covariance matrix

Variable	*Value*	*ACCURACY*	*ANFOL*	*ESGSCORE*	*VUL*
ACCURACY	Estimate	1	-0.0123	-0.0332	-0.000161
	Standard error		0.0163	0.0163	0.0163
	t-value		-0.755	-2.0332	-0.00987
	p-value		0.4503	**0.042**	0.9921
ANFOL	Estimate		1	0.4668	-0.3351
	Standard error			0.0128	0.0145
	t-value			36.5684	-23.1228
	p-value			**< 0.0001**	**< 0.0001**
ESGSCORE	Estimate			1	0.0413
	Standard error				0.0163
	t-value				2.5343
	p-value				**0.0113**
VUL					1

Note: VUL is the LSEG's ESG controversies score; ESGscore is the LSEG's ESG combined score; ACCURACY measures the financial analyst forecast accuracy and ANFOL is the number of financial analysts as defined in Appendix.

We find significant correlation and covariance at the 1% level between the analyst following and *VUL*, our independent variables of interest. The correlation and covariance are positive for the *ESGSCORE* and negative for *VUL*, our vulnerability index.

4.2.2. Differences in means and medians

We conduct further univariate analysis to find preliminary support for our hypotheses. For this purpose, we split our sample using the ESG scores and the *VUL* score. We use the median (mean) to code firms as HighESG (HighVUL) and LowESG (LowVUL). Using these classifications, we test the difference in means and medians for our two dependent variables (*ANFOL* and *ACCURACY*). We present our results for differences in means in Table 6.

Table 6. Differences in means

Variable	*HighESG (N = 1828)*	*LowESG (N = 1926)*	*t-value (high-low)*	*HighVUL (N = 3012)*	*LowVUL (N = 742)*	*t-value (high-low)*
ACCURACY	0.394	1.141	-1.06	0.815	0.623	0.40
ANFOL	2.662	2.119	24.83***	2.268	2.854	-21.43***

*Note: VUL is the LSEG's ESG controversies score; ESGscore is the LSEG's ESG combined score; ACCURACY measures the financial analyst forecast accuracy and ANFOL is the number of financial analysts as defined in Appendix. ***, **, and * represent the level of significance at 1%, 5%, and 10%, respectively.*

We find significant differences in mean analyst following between firms with high ESG scores (p-value < 0.0001) and those with low ESG scores. We also find significant but negative differences in analyst coverage for firms with high *VUL* (p-value < 0.0001) scores and those with low scores. We do not find any significant differences in means of forecast accuracy between firms with high ESG or *VUL* scores. We present our results for differences in medians in Table 7.

Table 7. Differences in medians

Variable	*HighESG (N = 1828)*	*LowESG (N = 1926)*	*Z-value (high-low)*	*HighVUL (N = 3012)*	*LowVUL (N = 742)*	*Z-value (high-low)*
ACCURACY	0.0024	0.0039	9.150***	0.0033	0.0025	3.930***
ANFOL	2.773	2.079	23.207***	2.303	2.996	-20.304***

*Note: VUL is the LSEG's ESG controversies score; ESGscore is the LSEG's ESG combined score; ACCURACY measures the financial analyst forecast accuracy and ANFOL is the number of financial analysts as defined in Appendix. ***, **, and * represent the level of significance at 1%, 5%, and 10%, respectively.*

Results for median differences differ from those of the mean differences in that both accuracy and analyst following are significantly different for the high and low ESG and *VUL* firm scores. These results provide preliminary support for our *H1* and *H2*. Firms with higher ESG scores (and low *VUL*) have higher analyst following in support of *H1* and have better accuracy in support of *H2*.

Prior literature (Sautner et al., 2023) classifies industries according to their level of exposure to the effects of climate change. Industries in the following 2-digit SIC codes are deemed to be more exposed: 01, 02, 07,10, 12, 13, 14, 20, 21, 37, 44, 45, 46, 47, 49, and 50. We use this classification and test of differences to calibrate our vulnerability index. We partition our sample into high and low exposure based on whether the firm is in these industries (coded 1) or not (coded 0). We present our results in Table 8.

Table 8. Test of differences between high and low exposure to climate change effects

Variable	*High exposure*		*Low exposure*		*Difference in means (1–0) t-value (p-value)*	*Difference in medians (1–0) Z-value (p-value)*
	Mean	*Median*	*Mean*	*Median*		
VUL	0.843	1.00	0.898	1.000	-4.05***	-4.09***
ESGSCORE	0.484	0.476	0.477	0.470	0.67	0.74

*Note: VUL is the LSEG's ESG controversies score; ESGscore is the LSEG's ESG combined score. ***, **, and * represent the level of significance at 1%, 5%, and 10%, respectively.*

Our findings in Table 8 indicate that there are significant mean and median differences at the 1% level in the variable *VUL* (our vulnerability index) between firms in high-exposure industries and those in low-exposure industries. We do not find significant differences in either means or medians for the ESG combined score. This could mean that climate change vulnerability does not influence the level of voluntary ESG disclosures, which can also be interpreted as the quality of corporate governance.

4.3. Multivariate analysis

We start our analysis by calibrating our dataset by estimating Model 1 with the ESG score. This estimation seeks to find out whether our interpretation of the ESG score is in line with the literature.

We present our results in Table 9. The highest variance inflation value in this estimation is 2.90. Consistent with our expectations, we find that our ESG score variable is significant and positive at the 1% level.

Table 9. Regression results for calibrating Model 1

Variable	*Coefficient*	*t-value*	*p-value*
Dependent variable — Analyst following			
Intercept	0.277***	6.62	< 0.0001
ESGSCORE	0.240***	8.84	< 0.0001
$ANFOL_{T-1}$	0.863***	137.93	< 0.0001
$EPSFX_{t-1}$	-0.003***	-6.6	< 0.0001
$EPSCH_{t-1}$	0.000*	1.66	0.0978
$SALCH_{t-1}$	0.009	1	0.3152
AR_{t-1}	0.062***	7.19	< 0.0001
$EPSVOL_{t-1}$	0.001	0.89	0.3753
$RETVAR_{t-1}$	0.277***	6.62	< 0.0001
N	3751		
Fixed year effects	Yes		
Fixed industry effects	Yes		
F-value (p-value)	2175.1 (< 0.0001)		
Adjusted R-square	0.8743		

*Note: ESGSCORE, the variable of interest in this estimation, is the LSEG's ESG combined score. All other variables are as defined in Appendix. ***, **, and * represent the level of significance at 1%, 5%, and 10%, respectively.*

This finding suggests that firms with high ESG scores are covered more by financial analysts. This is expected because such firms are perceived to have higher-quality corporate governance. Higher ESG scores imply that there is a concerted effort to improve the information environment through voluntary ESG disclosure. Therefore, our finding is consistent with previous research that documents analysts' preference for firms with better information environments (Bhushan, 1989; Bushman et al., 2005; Lang & Lundholm, 1996). Hence, our interpretation of the ESG score is in line with the existing literature.

We then proceed to test our first hypothesis by estimating Model 1. We present our results in Table 10. The highest variance inflation value in this estimation is 2.91.

Table 10. Regression results for Model 1 (Vulnerability index)

Variable	*Coefficient*	*t-value*	*p-value*
Dependent variable — Analyst following			
Intercept	0.234***	4.71	< 0.0001
VUL	-0.067***	-3.62	0.0003
$ANFOL_{T-1}$	0.823***	116.81	< 0.0001
TA_{t-1}	0.043***	12.84	< 0.0001
$EPSFX_{t-1}$	-0.003***	-6.85	< 0.0001
$EPSCH_{t-1}$	0.001*	1.84	0.0665
$SALCH_{t-1}$	0.010	1.22	0.2217
AR_{t-1}	0.070***	8.23	< 0.0001
$EPSVOL_{t-1}$	0.001	0.57	0.5661
$RETVAR_{t-1}$	-0.407	-0.99	0.32
N	3751		
Fixed year effects	Yes		
Fixed industry effects	Yes		
F-value (p-value)	2093.16 (< 0.0001)		

*Note: VUL, the variable of interest, is the LSEG's ESG controversies score. All other variables are as defined in Appendix. ***, **, and * represent the level of significance at 1%, 5%, and 10%, respectively.*

Our independent variable of interest is *VUL*, a measure of climate change vulnerability. *VUL* is the LSEG's variable ESG controversies score. This score measures a company's exposure to ESG controversies and negative events reflected in global media. We find results that are consistent with our expectation; significantly lower *VUL* at 1% for increasing analyst following.

We then test *H2*. In *H2*, we argue that firms with higher vulnerability to the effects of climate change would be associated with less accurate financial analyst forecasts compared to those with lower vulnerability. We fail to find support for *H2* using a full sample. Owing to the noisiness of our measure of climate change vulnerability, we decide to partition our sample into the high-exposure and low-exposure industries. Therefore, we estimate our Model 2 three times, with the full sample, a high-exposure sub-sample, and a low-exposure sub-sample. Our model loses power in the high-exposure estimation due to the drastically reduced sample size. From the computation of our dependent variable, more accurate forecasts are indicated by decreasing values of *ACCURACY*. We show our results in Table 11.

We find multivariate support for *H2* for the high-exposure partition of our sample. The *VUL* variable is negative and significant at the 6% level. Furthermore, the adjusted r-squared increases from a low of 10% in the full sample estimation to 66% in the high-exposure sub-sample. Further to our preliminary univariate support for this hypothesis in our test for differences in medians and considering the size of our sample and the noisy nature of our proxy for climate change vulnerability, we interpret this finding to be adequate support for *H2*.

Table 11. Regression results for Model 2

Variable	*Full sample*		*Low exposure*		*High exposure*	
	β	*p-value*	*β*	*p-value*	*β*	*p-value*
Dependent variable — ACCURACY						
Intercept	1.697	0.496	3.921	0.364	-1.204	0.409
VUL	0.344	0.829	0.484	0.786	**-1.112***	**0.062**
LOSS	3.066***	0.001	3.121***	0.003	1.717***	< 0.0001
MKV	0.219	0.287	0.271	0.206	0.051	0.664
LEV	-0.353	0.858	-0.216	0.910	0.545	0.575
ANFOL	-0.152	0.802	-0.220	0.736	0.074	0.791
RDV	-1.671	0.707	-2.123	0.640	-13.160**	0.016
CEODUALITY	0.010	0.996	-0.139	0.947	1.716*	0.060
BIND	0.791	0.883	0.919	0.884	0.479	0.761
BDSIZE	-0.448	0.270	-0.452	0.306	0.165	0.366
DISP	0.393***	< 0.0001	0.387***	< 0.0001	0.261***	< 0.0001
ACTEPSVOL	0.003	0.319	0.002	0.550	0.024***	< 0.0001
BIG6	-1.139	0.262	-1.124	0.298	-0.167	0.724
ICMW	-0.924	0.555	-0.804	0.651	-0.373	0.482
N	3751		3386		365	
Fixed year effects	Yes		Yes		Yes	
Fixed industry effects	Yes		Yes		Yes	
F-value (p-value)	2.5 (< 0.0001)		2.94 (< 0.0001)		42.76 (< 0.0001)	
Adjusted R-square	0.0103		0.0097		0.6610	

*Note: VUL, the variable of interest, is the LSEG's ESG controversies score. All other variables are as defined in Appendix. ***, **, and * represent the level of significance at 1%, 5%, and 10%, respectively.*

4.4. Additional analysis

We conduct further analysis to ensure robustness and a better understanding of our findings. First, we repeat our analysis using a winsorized dataset for variables identified as having potential outlier concerns in the univariate analysis. We winsorize at 5% and 95%. Our untabulated results do not change from those of the main analysis.

Second, we examine whether there are mediating effects in our variable relationships. We find that the ESG score mediates the analyst-following model. However, the percentage mediated is only 1.5%. Though this is statistically significant at the 1% level, we do not consider it economically significant. There are no significant mediation effects on our accuracy and analyst following relationships with variable *VUL*.

5. DISCUSSION OF THE RESULTS

We now discuss our results starting with the univariate analysis. The positive and significant correlation between analyst following and ESG score is in line with prior research findings that analysts prefer firms with high-quality disclosure (Lang & Lundholm, 1996) and with an improved information environment (Bushman et al., 2005). Higher ESG scores imply a better information environment and improved management disclosures. The negative and significant correlation and covariance between the analyst following and *VUL*, the vulnerability index, provides support for *H1*. Decreasing values of *VUL* means increasing ESG controversies. Hence, our finding is also to be expected because analysts shy away from firms with increased information acquisition costs, and without this information, it is more difficult to forecast their earnings (Graham et al., 2005). The negative and significant correlation between *ACCURACY* and ESG score is consistent with the literature. This is because forecast accuracy increases with improving information environment and disclosure; this would be the case for companies with higher ESG scores.

The positive and significant correlation and covariance at the 5% level between the ESG score and *VUL*, our vulnerability index suggests that that firms with controversies make concerted efforts to improve their ESG disclosures. This is reasonable given that the controversies would be a critical concern for investors aside from making it difficult for analysts to make accurate forecasts. This may also be interpreted as per the argument in Anantharaman and Zhang (2011), where they indicate that managers tradeoff between the benefits of analyst coverage and the cost of disclosure; furthermore, where legal liability is involved, as, in case of ESG controversies, managers have incentives to make disclosures related to the potentially litigious issues.

The significantly higher average and median analyst following among firms with high ESG scores (low *VUL* index) means that, on average, firms with high ESG scores are more likely to benefit from higher coverage by financial analysts compared to those with low scores. This is consistent with analysts preferring firms with better disclosure (information environment) as documented in prior literature (Lang & Lundholm, 1996). Furthermore, it means that analysts shy away from firms with high vulnerabilities. Going by prior literature, we attribute this to the related variability in earnings or the unpredictable future expected earnings.

Our results show that firms operating in industries that are more exposed to climate change effects have elevated levels of controversies (in our case, vulnerability) and have a significantly lower *VUL* score than those in other industries. We interpret this to mean our proxy for climate change vulnerability, *VUL*, though noisy, captures differences in the effects of climate change. This adds credence to our analysis and results at the multivariate level.

In our Model 1 estimation, we find that firms with climate change-related vulnerabilities lose about 7% of their analyst following. This is consistent with the documented behavior of analysts when the cost of obtaining information (Anantharaman & Zhang, 2011; Graham et al., 2005; Lang & Lundholm, 1996) is high or when the earnings are likely to fluctuate. This finding supports *H1* that firms with higher climate change risks have fewer financial analysts compared to those with lower risks. Our results provide empirical evidence that climate change effects significantly affect the use of financial information.

Our findings in Model 2 estimation show that increasing vulnerabilities (reducing *VUL* values) are significantly associated with increasing values of *ACCURACY*, which means reducing forecast accuracy. This is in support of our argument in *H2*. In addition, we demonstrate that this effect is not observed in firms operating in industries not deemed to be at high climate change risk. In and of itself, this is telling; the effects of climate change do not end at the level of resource use and exploitation or the related litigations or controversies. Hence, it matters to investors and users of information whether a company is in a high climate change risk industry or not. This finding also adds to the understanding of financial analysts as sophisticated users of company information to the extent that they incorporate these future-related aspects into their forecasts.

We recognize that our analysis is limited due to the noisy nature of our proxy for climate change vulnerability. This is because the ESG controversies index available from LSEG also includes components that are not related to climate change issues. Although we have taken steps to allay fears related to this limitation, we recommend that further research could benefit from using a less noisy index. Moreover, using indices that measure more specific climate change vulnerabilities (e.g., carbon emissions, energy use, environmental-related controversies) might prove more insightful. Another limitation of our paper is that the ESG vulnerabilities may change over time depending on the climate change dynamics and due to the continued exploitation of resources and human activity. This potentially causes a discrepancy in the variables. Future research may consider how to incorporate this dynamic aspect in the research design.

Notwithstanding these limitations, our results differ from those in previous studies in two several ways. First, previous studies have not used the ESG controversies score to proxy for climate change vulnerability. Second, previous studies have not examined the behavior of financial analysts and the accuracy of their forecasts in relation to ESG performance and controversies. Third, our results add to our understanding of financial analyst behavior and to the application of efficient market hypothesis in that we have empirical evidence that financial analysts incorporate climate change effects in their algorithms as they prepare investor recommendations.

6. CONCLUSION

This paper sought to determine whether companies with climate change vulnerability issues suffer from declining analyst following. Another question was whether analyst forecast accuracy is affected by climate change vulnerability. Our findings show that firms with vulnerabilities significantly lose analyst following and have significantly less accurate analyst forecasts. These are important findings for both investors and executives. For the investors, it is important because they suggest that they must use analyst forecasts from such companies with caution. For the executives, these results mean that they must take a keener look at their disclosures when making decisions on how to attract analysts, as documented by Anantharaman and Zhang (2011). This would provide more appealing information to investors.

Our results bring to the fore an additional understanding of how climate change effects directly affect both the information environment and the behavior of financial analysts. These results further suggest that the effects of climate change do not only affect firm operations but also how firm executives and users of information behave. These results also point to the need to better understand the dynamics of climate change beyond the issues of climate change governance.

Our research, nevertheless, has several limitations that future research would focus to diminish. First, our proxy for climate change vulnerability includes controversies that are not related to climate change making it quite noisy. Second, our sample size is relatively small; a larger sample size may tease out other effects that we could not find. Third, our sample firms are only in one geographical area, the United States. Repeating the same research in other regions, especially in the Global South may provide better insights than we were able to find.

REFERENCES

Alsaifi, K., Elnahass, M., Al-Awadhi, A. M., & Salama, A. (2022). Carbon disclosure and firm risk: Evidence from the UK corporate responses to climate change. *Eurasian Business Review, 12*, 505–526. https://doi.org/10.1007/s40821-021-00190-0

Alvarez, I. G. (2012). Impact of CO_2 emission variation on firm performance. *Business Strategy and the Environment, 21*(7), 435–454. https://doi.org/10.1002/bse.1729

Amran, A., Periasamy, V., & Zulkafi, A. H. (2014). Determinants of climate change disclosure by developed and emerging countries in Asia Pacific. *Sustainable Development, 22*(3), 188–204. https://doi.org/10.1002/sd.539

Anantharaman, D., & Zhang, Y. (2011). Cover me: Managers' responses to changes in analyst coverage in the post-regulation FD period. *The Accounting Review, 86*(6), 1851–1885. https://doi.org/10.2308/accr-10126

Angeli, M., Archer, C., Batten, S., Cesa-Bianchi, A., D'Aguanno, L., Haberis, A., Löber, T., Maxwell, S., Sajedi, R., van der Merwe, M., Wanengkirtyo, B., & Young, C. (2022, October 21). *Climate change: Possible macroeconomic implications*. Bank of England. https://www.bankofengland.co.uk/quarterly-bulletin/2022/2022-q4/climate-change-possible-macroeconomic-implications
Aydoğmuş, M., Gülay, G., & Ergun, K. (2022). Impact of ESG performance on firm value and profitability. *Borsa Istanbul Review, 22*(S2), S119–S127. https://doi.org/10.1016/j.bir.2022.11.006
Babcock, A., He, A., & Ramani, V. (2022). Building investor trust in net zero. *Journal of Applied Corporate Finance, 34*(2), 52–59. https://doi.org/10.1111/jacf.12505
Ballesteros, F., Hüttel, A., Neuholf, K., & Marchewitz, C. (2023). On the way to climate neutrality: scenarios can facilitate the transition of companies and the financial sector. *DIW Weekly Report, 13*(25), 183–190. https://www.econstor.eu/bitstream/10419/278043/1/1860132898.pdf
Barton, D., Bailey, J., & Zoffer, J. (2016). *Rising to the challenge of short-termism*. Focusing Capital on the Long Term (FCLT GlOBAL). https://www.fcltglobal.org/wp-content/uploads/fclt-global-rising-to-the-challenge.pdf
Berk, J., & DeMarzo, P. (2011). *Corporate finance* (2nd ed.). Prentice Hall.
Bhushan, R. (1989). Firm characteristics and analyst following. *Journal of Accounting and Economics, 11*(2–3), 255–274. https://doi.org/10.1016/0165-4101(89)90008-6
Borghei, Z. (2021). Carbon disclosure: A systematic literature review. *Accounting & Finance, 61*(4), 5255–5280. https://doi.org/10.1111/acfi.12757
Bouchet, V., Dayan, H., & Contouz, C. (2022). Finance and climate science: Worlds apart? *Journal of Risk Research, 25*(2), 176–197. https://doi.org/10.1080/13669877.2021.1913635
Burke, J. J., Hoitash, R., & Hoitash, U. (2019). Auditor response to negative media coverage of client environmental, social, and governance practices. *Accounting Horizons, 33*(3), 1–23. https://doi.org/10.2308/acch-52450
Bushman, R, M., Piotroski, J. D., & Smith, A. J. (2005). Insider trading restrictions and analysts' incentives to follow firms. *Journal of Finance, 60*(1), 35–66. https://doi.org/10.1111/j.1540-6261.2005.00724.x
Byard, D., Li, Y., & Weintrop, J. (2006). Corporate governance and the quality of financial analysts' information. *Journal of Accounting and Public Policy, 25*(5), 609–625. https://doi.org/10.1016/j.jaccpubpol.2006.07.003
Chung, K. H., & Jo, H. (1996). The impact of security analysts' monitoring and marketing functions on the market value of firms. *Journal of Financial and Quantitative Analysis, 31*(4), 493–512. https://doi.org/10.2307/2331357
Clerc, L. (2021). Managing climate change risks: The role of governance and scenario analysis. *Journal of Risk Management in Financial Institutions, 15*(1), 38–50. https://doi.org/10.69554/QMHH8100
Corvellec, H., Hultman, J., Jerneck, A., Arvidsson, S., Ekroos, J., Wahlberg, N., & Luke, T. W. (2021). Resourcification: A non-essentialist theory of resources for sustainable development. *Sustainable Development, 29*(6), 1249–1256. https://doi.org/10.1002/sd.2222
Cummings, B. (2022). A retrospective glance at risks to the finance industry. *Journal of Financial Planning, 35*(1). https://www.proquest.com/openview/3a7f868da59cce8a8cd44743a4907ee5
Deschenes, O. (2022). The impact of climate change on mortality in the United States: Benefits and costs of adaptation. *Canadian Journal of Economics, 55*(3), 1227–1249. https://doi.org/10.1111/caje.12609
Egan, P. J., Konisky, D. M., & Mullin, M. (2022). Ascendant public opinion: The rising influence of climate change on Americans' attitudes about the environment. *Public Opinion Quarterly, 86*(1), 134–148. https://doi.org/10.1093/poq/nfab071
Francis, J. R., Neuman, S. S., & Newton, N. J. (2019). Does tax planning affect analysts' forecast accuracy? *Contemporary Accounting Research, 36*(4), 2663–2694. https://doi.org/10.1111/1911-3846.12515
Girón, A., & Ivanova, A. (2023). Climate action, institutional investors, and just transition. *Journal of Economic Issues, 57*(2), 575–585. https://doi.org/10.1080/00213624.2023.2202142
Gough, J. (2023). Climate change and the global economy. *World Economics Journal, 24*(1), 35–69. https://www.world-economics-journal.com/Papers/Climate-Change-and-the-Global-Economy.aspx?ID=885
Graham, J. R., Harvey, C. R., & Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics, 40*(1–3), 3–73. https://doi.org/10.1016/j.jacceco.2005.01.002
Greer, K., Turco, K., & Wallace, D. (2022). CFOs create value for climate adaptation & resilience in agency operations. *Journal of Government Financial Management, 70*(4), 26–31.
Griffin, P. A., Lont, D. H., & Sun, E. Y. (2017). The relevance to investors of greenhouse gas emission disclosures. *Contemporary Accounting Research, 34*(2), 1265–1297. https://doi.org/10.1111/1911-3846.12298
Grove, H., Clouse, M., & Xu, T. (2024). Board oversight: Required ESG for public companies in Europe. *Corporate Ownership & Control, 21*(1), 72–81. https://doi.org/10.22495/cocv21i1art7
Hadzi-Velkova, B., Gavrovska, M. M., & Shterieva, M. S. (2022). Climate change and its implications on the financial risks. *Economic Development, 4*, 6–20. https://doi.org/10.55302/ED2224406hv
Hale, L. H. (2022). Energy and climate change. *The International Economy*, 50–67. http://www.international-economy.com/TIE_W22_Hale.pdf
Han, Y.-G., Huang, H.-W., Liu, W.-P., & Hsu, Y.-L. (2023). Firm-value effects of carbon emissions and carbon disclosures: Evidence from Taiwan. *Accounting Horizons, 37*(3), 171–191. https://doi.org/10.2308/HORIZONS-18-164R
He, J. J., & Tian, X. (2013). The dark side of analyst coverage: The case of innovation. *Journal of Financial Economics, 109*(3), 856–878. https://doi.org/10.1016/j.jfineco.2013.04.001
He, R., Luo, L., Shamsuddin, A., & Tang, Q. (2022). Corporate carbon accounting: A literature review of carbon accounting research from the kyoto protocol to the Paris agreement. *Accounting & Finance, 62*(1), 261–298. https://doi.org/10.1111/acfi.12789
Heal, G., & Millner, A. (2014). Reflections: Uncertainty and decision making in climate change economics. *Review of Environmental Economics and Policy, 8*(1), 120–137. https://doi.org/10.1093/reep/ret023
Healy, P. M., & Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: a review of the empirical disclosure literature. *Journal of Accounting and Economics, 31*(1-3), 405–440. https://doi.org/10.1016/S0165-4101(01)00018-0

Hoang, K. (2022). How does corporate R&D investment respond to climate policy uncertainty? Evidence from heavy emitter firms in the United States. *Corporate Social Responsibility and Environmental Management,29*(4), 936–949. https://doi.org/10.1002/csr.2246
Hong, H., & Kacperczyk, M. (2009). The price of sin: The effects of social norms on markets. *Journal of Financial Economics, 93*(1), 15–36. https://doi.org/10.1016/j.jfineco.2008.09.001
Huang, H. H., Kerstein, J., & Wang, C. (2018). The impact of climate risk on firm performance and financing choices. *Journal of International Business Studies, 49*, 633–656. https://doi.org/10.1057/s41267-017-0125-5
Huwei, W., Shuai, C., & Chien-Chiang, L. (2023). Impact of low-carbon city construction on financing, investment, and total factor productivity of energy-intensive enterprises. *The Energy Journal, 44*(2), 79–102. https://doi.org/10.5547/01956574.44.2.hwen
Irani, A. J., & Karamanou, I. (2003). Regulation fair disclosure, analyst following, and analyst forecast dispersion. *Accounting Horizons, 17*(1), 15–29. https://doi.org/10.2308/acch.2003.17.1.15
Jo, H., & Harjoto, M. (2014). Analyst coverage, corporate social responsibility, and firm risk. *Business Ethics: A European Review, 23*(3), 272–292. https://doi.org/10.1111/beer.12051
Johnson, J. A., Theis, J., Vitalis, A., & Young, D. (2020). The influence of firms' emissions management strategy disclosures on investors' valuation judgments. *Contemporary Accounting Research, 37*(2), 642–664. https://doi.org/10.1111/1911-3846.12545
Kalyani, S., & Mondal, R. (2024). Is ESG disclosure creating value propositions for the firms? An SLR and meta-analysis of how ESG affects the financials of a firm. *Corporate Ownership & Control, 21*(1), 96–117. https://doi.org/10.22495/cocv21i1art9
Kanagaretnam, K., Lobo, G., & Zhang, L. (2022). Relationship between climate risk and physical and organizational capital. *Management International Review, 62*, 245–283. https://doi.org/10.1007/s11575-022-00467-0
Kantur, Z., & Ozcan, G. (2022). Monetary policymaking under climate uncertainty. *Business and Economics Research Journal, 13*(4), 579–591. https://doi.org/10.20409/berj.2022.390
Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies, 33*(3), 1067–1111. https://doi.org/10.1093/rfs/hhz137
Lang, M. H., & Lundholm, R. L. (1996). Corporate disclosure policy and analyst behavior. *The Accounting Review, 71*(4), 467-492. https://www.jstor.org/stable/248567
Leimbach, M., & Bauer, N. (2022). Capital markets and the costs of climate policies. *Environmental Economics and Policy Studies, 24*, 397–420. https://doi.org/10.1007/s10018-021-00327-5
Lim, T. (2001). Rationality and analysts' forecast bias. *The Journal of Finance, 56*(1), 369–385. https://doi.org/10.1111/0022-1082.00329
Macchi, C., & van Zeben, J. (2021). Business and human rights implications of climate change litigation: Milieudefensie et al. v Royal Dutch Shell. *Review of European, Comparative & International Environmental Law, 30*(3), 409–415. https://doi.org/10.1111/reel.12416
Málits, P., El-Meouch Nedim, M., & Drabancz, A. (2022). Possible real economic consequences of financial actors' attitudes towards climate change and realized risks. *Public Finance Quarterly, 67*(3), 430–447. https://doi.org/10.35551/PFQ_2022_3_7
Mankirar, D. (2023, May 11). How TNFD's new core metrics can help corporations and investors measure nature impacts and dependency. *S&P Global Sustainable1.* https://www.spglobal.com/esg/insights/blog/how-tnfd-s-new-core-metrics-can-help-corporations-and-investors-measure-nature-impacts-and-dependency
Mburu, H. K., & Tang, A. P. (2018). Voluntary clawback adoption and analyst following, forecast accuracy, and bias. *Journal of Accounting and Finance, 18*(2), 106–122. https://doi.org/10.33423/jaf.v18i2.402
Milkau, U. (2022). Climate change risk: Demands and expectations imposed on banks. *Journal of Risk Management in Financial Institutions, 15*(3), 278–300. https://doi.org/10.69554/AVBW8233
Ouazad, A., & Kahn, M. E. (2022). Mortgage finance and climate change: Securitization dynamics in the aftermath of natural disasters. *The Review of Financial Studies, 35*(8), 3617–3665. https://doi.org/10.1093/rfs/hhab124
Ozkan, A., Temiz, H., & Yildiz, Y. (2011). Climate risk, corporate social responsibility, and firm performance. *British Journal of Management, 34*(4), 1791–1810. https://doi.org/10.1111/1467-8551.12665
Panfilo, S., & Krasodomska, J. (2022). Climate change risk disclosure in Europe: The role of cultural-cognitive, regulative, and normative factors. *Accounting in Europe, 19*(1), 226–253. https://doi.org/10.1080/17449480.2022.2026000
Qian, C., Lu, L. Y., & Yu, Y. (2019). Financial analyst coverage and corporate social performance: Evidence from natural experiments. *Strategic Management Journal, 40*(13), 2271–2286. https://doi.org/10.1002/smj.3066
S&P Global Market Intelligence. (2021). *Leading climate scenario analysis for transition and credit risk.* https://www.spglobal.com/marketintelligence/en/documents/mi-risk-983425-climate-credit-analytics.pdf
Saka, C., & Oshika, T. (2014). Disclosure effects, carbon emissions and corporate value. *Sustainability Accounting, Management and Policy Journal, 5*(1), 22–45. https://doi.org/10.1108/SAMPJ-09-2012-0030
Sautner, Z., Van Lent, L., Vilkov, G., & Zhang, R. (2023). Firm-level climate change exposure. *Journal of Finance, 78*(2), 1449–1498. https://doi.org/10.1111/jofi.13219
Serafeim, G., & Yoon, A. (2022). Which corporate ESG news does the market react to? *Financial Analysts Journal, 78*(1), 59–78. https://doi.org/10.1080/0015198X.2021.1973879
Simnett, R., Nugent, M., & Huggins, A. L. (2009). Developing an international assurance standard on greenhouse gas statements. *Accounting Horizons, 23*(4), 347–363. https://doi.org/10.2308/acch.2009.23.4.347
Sobehart, J. R. (2021). Quantifying climate risk uncertainty in competitive business environments. *Journal of Risk Management in Financial Institutions, 15*(1), 26–37. https://doi.org/10.69554/MXJU8050
Sullivan, R., & Gouldson, A. (2012). Does voluntary carbon reporting meet investors' needs? *Journal of Cleaner Production, 36*, 60–67. https://doi.org/10.1016/j.jclepro.2012.02.020
Tankov, P., & Tantet, A. (2019). *Climate data for physical risk assessment in finance.* https://doi.org/10.2139/ssrn.3480156
Venturini, A. (2022). Climate change, risk factors and stock returns: A review of the literature. *International Review of Financial Analysis, 79*, Article 101934. https://doi.org/10.1016/j.irfa.2021.101934
Wade, B., & Griffiths, A. (2022). Exploring the cognitive foundations of managerial (climate) change decisions. *Journal of Business Ethics, 181*, 15–40. https://doi.org/10.1007/s10551-021-04855-8

Whieldon, E., Yap, S., Raikwar, L., & Desme, G. (2023). How the world's largest companies depend on nature and biodiversity. In *S&P Global sustainability quarterly: Accelerating progress in the world with essential sustainability intelligence* (pp. 6–17). S&P Global. https://www.spglobal.com/esg/insights/featured/sustainability-journal/sustainability-q2-2023-report.pdf

Wu, J. S., & Zang, A. Y. (2009). What determine financial analysts' career outcomes during mergers? *Journal of Accounting and Economics, 47*(1–2), 59–86. https://doi.org/10.1016/j.jacceco.2008.11.002

Yu, F. (2008). Analyst coverage and earnings management. *Journal of Financial Economics, 88*(2), 245–271.

Zilja, F., Adarkwah, G. K., & Sabel, C. A. (2022). Do environmental policies affect MNEs' foreign subsidiary investments? An empirical investigation. *Management International Review, 62*, 53–102. https://doi.org/10.1007/s11575-021-00458-7

APPENDIX

Table A.1. Variable definitions

Variables	*Definitions*
ACCURACY	The absolute value of the difference between forecast and actual EPS scaled by the beginning stock price.
VUL	Company climate change vulnerability index proxied by LSEG ESG controversies score.
ESGSCORE	The LSEG combined ESG score.
ACTEPSVOL	Earnings volatility is measured by the standard deviation of actual EPS (from IBES) for the past five years scaled by the beginning stock price.
$ANFOL_{T-1}$	Total analyst following for firm *i* over the year *t* - 1.
AR_{t-1}	Firm *i*'s compounded return over a one-year period ending in the third quarter of period *t* less the compounded return for the value-weighted market index for the same period.
BDSIZE	The natural logarithm of the number of directors on the board.
BIG6	Dummy variable coded 1 if the auditor for the year was a Big 6 audit firm (KPMG, Ernst & Young, PricewaterhouseCoopers — PwC, Deloitte & Touche, Grant Thornton, or BDO USA) or 0 otherwise.
BIND	Proportion of independent directors on the board.
CEODUALITY	Dummy variable coded 1 if the CEO is also the chair of the board and 0 otherwise.
DISP	Standard deviation of the year analyst forecasts scaled by the beginning stock price.
$EPSFX_{t-1}$	Annual EPS before discontinued operations and extraordinary items for firm *i* in year *t* - 1.
$EPSCH_{t-1}$	Change in annual EPS for firm *i* in period *t* - 1 divided by *t* - 2 beginning stock price.
$EPSVOL_{t-1}$	Standard deviation of annual EPS (using EPS from *t* through *t* - 4 for firm *i* divided by the stock price at the beginning of year *t* - 4.
ESGSCORE	The LSEG's ESG combined score that is based on the reported information in environmental, social, and corporate governance pillars.
ICMW	A dummy variable equal to 1 if the firm had internal control material weaknesses in the last three years and 0 otherwise.
IND	Dummy variables based on Fama and French industry classification to control for industry-specific effects.
LEV	Measures leverage and is given by long-term debt scaled by lagged total assets.
LOSS	A dummy variable coded 1 if the firm reported a loss during the year and 0 otherwise.
MKV	Measures firm growth opportunities defined as market value (outstanding shares multiplied by closing stock price) scaled by book value (total assets).
RDV	R&D intensity computed as R&D plus advertising expenditure scaled by operating expenses; R&D and advertising expenditure are set to 0 if missing.
$RETVAR_{t-1}$	Standard deviation of daily firm *i* return for a one-year period ending in the third quarter of each period.
$SALCH_{t-1}$	Change in annual net sales revenue for firm *i* in period *t* - 1 divided by *t* - 2 net sales.
TA_{t-1}	The natural logarithm of total assets for firm *i* in year *t* - 1.
YR	Dummy variable to control for year-fixed effects.