Does Climate Change Affect Misreporting?

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Abstract

This paper examines the impact of climate change on companies' misreporting behaviour. We find that companies with higher levels of climate change exposure are more likely to misreport their financial statements. We employ the fraud triangle to explore potential mechanisms underlying this behaviour. Climate change provides opportunities for misreporting, as it can significantly reduce accounting comparability due to the need for professional judgment in accounting treatments related to climate change, especially since Generally Accepted Accounting Principles (GAAP) do not explicitly address climate-related issues. Through the pressure channel, companies facing greater climate exposure experience higher cash flow shortfalls, reduced revenue-generating capabilities, and increased insolvency risks, which might compel management to engage in misreporting to appease stakeholders, secure financing, or meet market expectations. This result is more pronounced in firms that possess higher asset tangibility, are smaller, face lower environmental litigation risks, issue fewer equity instruments in a given year, have high market leverage and are headquartered in regions where people have low climate change belief.

Our research is the first study that shows the link between corporate misreporting behaviour and climate change. For policymakers, we highlight the need for accounting standard-setters to incorporate explicit guidelines on climate-related issues, underscoring a significant gap in current GAAP regulations.

JEL codes: *M20, M41*

Keywords: Climate Change Exposure, Misreporting, Accounting Irregularities, Misstatement, Accounting Comparability, Financial Pressure, Financial Fraud

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1. Introduction

The societal costs arising from climate-related effects are substantial and continue to increase. A growing body of literature has shown the economic consequence of climate change, including the pricing of stocks, bonds, real estate and capital structure (e.g., Bernstein et al., 2019; Painter, 2020; Seltzer et al., 2022; Ginglinger and Moreau, 2023), and the majority of institutional investors recognize climate change as an essential issue (Krueger et al. 2020). Despite the growing importance of climate change, little is known about its effect on firms' financial misreporting behaviour.

Identifying the rationale for misreporting is of the highest priority to investors, regulators, and professionals (Samuels, Taylor and Verrecchia, 2021b) as the phenomenon of financial misreporting reduces the effectiveness and stability of capital markets and can even bring fatal losses resulting from legal risks (e.g., investigations from U.S. Securities and Exchange Commission (SEC)). Amiram et al. (2018) extensively examines the existing literature on causes and consequences of financial reporting misconduct from legal, accounting, and financial perspectives. According to their findings, significant costs of such misconduct include increased cost of equity, higher perceptions of information risk, reduced informativeness of earnings, susceptibility to class action litigation, regulatory interventions by the SEC, and increased turnover among executives and directors. In the context of the deadweight loss that financial fraud causes for firms, a large body of academic literature investigates the determinants of misreporting. Our research presents an analytical and empirical investigation into the impact of firm level climate change on financial misreporting behaviour and validates the existence of the potential channel. Based on both regression and matching designs, and two sets of measurements of misreporting behaviour (misstatement and discretionary accrual), we find that companies with higher levels of climate change exposure are more likely to misreport their financial statements. Given the low frequency of financial fraud after the Sarbanes-Oxley Act (SOX), we construct a one-to-one matched sample by matching each misreporting firm year with a non-misreporting firm year based on the same

3 years, industry, and assets. Our results survive under several robustness checks and do not suffer from any endogeneity issues.

Using the fraud triangle framework, we investigate the potential mechanisms driving more misreporting behaviour. Climate change provides opportunities for misreporting, as it can reduce accounting comparability by introducing significant uncertainties in the valuation of assets and liabilities and more reliance on the need for professional judgment in accounting treatments related to climate change matter, especially since Generally Accepted Accounting Principles (GAAP) do not explicitly address climate-related issues. From a pressure perspective, companies heavily affected by climate change often face cash flow deficits, diminished revenue capabilities, and rising insolvency risk, which compel management to engage in misreporting to appease stakeholders, secure financing, and meet market expectations. The pressure to maintain capital confidence amid deteriorating financial conditions can incentivize management toward unethical decision-making.

Our cross-sectional tests further confirm that this relationship is more pronounced in firms with high asset tangibility, smaller size, in industries with low environmental litigation risk, those that issued low equity instruments, have high market leverage, and are headquartered in areas with lower awareness of climate change. Such analysis can also be used to gain insight into the theoretical channels and support our hypothesis on mechanisms that climate change affect accounting irregularities through reduced accounting comparability (opportunity channel) and higher operating uncertainty (pressure channel).

This research makes several contributions to the existing literature. First, current research in this field primarily focuses on measuring climate change (e.g., Daniel, Litterman, and Wagner, 2017; Engle et al., 2020), the implications for the cost of external capital (e.g., Chava, 2014; Huynh and Xia, 2021; Javadi and Masum, 2021), the capital market reaction to climate change (e.g., Hong, Li, and Xu, 2019; Bolton and Kacperczyk, 2021) and the pricing of real estate in relation to climate change (e.g., Bernstein, Gustafson, and Lewis, 2019; Baldauf, Garlappi, and Yannelis, 2020), and the incentives for 4 management equity (Hossain et al., 2022b). In response, and departing from extant literature, we extend that climate change is an important determinant of firms' financial misreporting behaviour. To our best knowledge, this study is the first to provide direct empirical on the relationship between climate change exposure and financial misreporting behaviour and provide the channel through which climate change affect financial misreporting behaviour. More importantly, we reveal that under the influence of climate change, management's manipulation of financial statements has exceeded the boundaries regulated by Generally Accepted Accounting Principles (GAAP). Second, these results enhance the body of research in accounting and finance that investigates the determinants of misreporting (Armstrong et al., 2013; Balakrishnan and Cohen, 2011; Burns et al., 2010; Efendi et al., 2007; Jia et al., 2014; Lennox and Pittman, 2010). The existing body of work on misreporting behaviour primarily examines the incentives (such as debt contracting, remuneration, and taxation) that managers might anticipate to some extent. In contrast, our research investigates a specific external incentive, climate change exposure. The results of our study indicate that a company's vulnerability to climate-related issue has a substantial impact on financial reporting behaviour. Finally, we make substantial practical contribution for policymakers by highlighting the need for accounting standard-setters to incorporate explicit guidelines on climaterelated issues, underscoring a significant gap in current GAAP regulations.

2. Related literature and hypotheses

2.1 Overview of the literature

This study closely relates to several literatures. Growing economic and finance literature has proved the negative implication of environmental hazards on firm productivity (e.g., Zhang et al., 2017; Somanathan et al., 2021; Li et al., 2021; Addoum et al., 2020). Building on these literatures, Concurrent studies further report evidence that climate change associated with corporate decisions and/or performance. For example, Barrot and Sauvagnat (2016) find that the natural disasters has negative impact on sales growth and their largest customers. Pankratz and Schiller (2022) argue weather shocks at supplier locations reduce the operating performance of suppliers and their customers. Similarly, using high temperatures exposure to proxy climate change, Pankratz et al. (2023) further shows evidence that higher exposure to extremely high temperatures leads to lower overall revenues and operating profits.

Our study also builds on the literature on how investors respond to climate change. Recent studies reveals that exposure to sea-level rise impacts property values, municipal bond yields, and underwriter fees (Baldauf et al., 2020; Bernstein et al., 2019). As investors are growing more concerned about the financial consequences of climate-related issue, companies with increased vulnerability to climate change face greater challenges in attracting investments from equity and debtor investors (Krueger et al., 2020; Stroebel and Wurgler, 2021). Supporting this view, using firm-level data, Ginglinger and Moreau (2023) observe bankers and bondholders increase the interest spreads when providing loans to companies that have the highest level of climate risk. The existing body of research also highlights that investor responses can be characterized by both overreactions and underreactions. For instances, Huynh and Xia (2023) find that investors in both the U.S. corporate bond and stock market overact to disaster exposure, resulting in depressed current bond and stock prices and consequently higher future returns. However, Hong et al. (2019) finds that investors exhibit an underreaction to the impact of drought conditions on the profitability of firms within the food sector. They observe that companies in countries facing severe drought trends not only shows weaker profit growth but also experience lower abnormal stock returns. This variability in investor behaviour underscores a potential inconsistency in how such phenomena are factored into market assessments and investment decisions.

Among accounting research, prior studies have primarily focus on disclosing climate-related matter (non-financial information) (e.g. Ferri et al., 2018; Flammer et al., 2021; Ilhan et al., 2023; Müller et al., 2024). We build on these literatures by examining how and why climate change is associated with the risk that financial statements are misreported. Our focus on the effect of climate change exposure on presenting financial information as a financial reporting risk factor is motivated by standard setters including the International Accounting Standards Board (IASB), the Financial Accounting Standards

Board (FASB) and the International Auditing and Assurance Standards Board (IAASB) have each published guidance and voice growing concern with regard to the threat climate change poses to transparent and reliability in financial reporting.

We focus on corporate fraud because financial misconduct leads to deadweight loss, including increased costs of equity capital, higher perceived information risk, lower information content of earnings, class action lawsuits, regulatory actions by the SEC, and higher executive and director turnover (Amiram et al., 2018). Despite billions of dollars in stakeholder losses due to financial misreporting, we still have a fairly limited understanding of many of the factors that lead managers to materially misreport their firm's performance (Trompeter et al., 2013). Prior literature generally relies on the logic of the fraud triangle (AICPA 2002) to explain misreporting. View through this lens, prior research has extensively investigated pressure or incentives to misreport. For example, Efendi et al. (2007) documents the likelihood of a misstated financial statement increases greatly when the CEO has very sizable holdings of in-the-money stock options due to CEO's incentive to maintain or increase the stock price in the pursuit of self-interest benefit, and Pittman and Zhao (2020) find that covenant restriction is positively associated with the probability of misstatements for avoiding covenant violations and relieve covenant restrictions. Monitoring effect has also received considerable attention. Big five audited firms serve as high-quality external monitoring role and could decrease the likelihood of corporate fraud (Lennox and Pittman, 2010). Furthermore, it is argued that market competition affect incidence of misreport as an efficient disciplinary (Balakrishnan and Cohen, 2011). Some prior studies focus on identifying attitude and culture associated with misreporting behaviour. Specifically, Schrand and Zechman (2012) discuss that executives exhibiting overconfidence are more prone to misreport. Likewise, McGuire et al., (2012) provide empirical evidence that firms headquartered in areas with stronger religious social norms are less inclined to misreport financial information, positing that prevailing social norms in such regions discourage managers from unethical business practices. However, the authors are unable to disentangle whether the external ecological environment contributes to GAAP-violating accounting treatments. To the extent that physical, transitioning and regulatory risks associated with climate change can lead to various negative consequences for affected firms, which erodes their profitability and financial stability, and investors are growing more concerned about the financial consequences of climate-related issue (Stroebel and Wurgler, 2021), the question naturally arises as to whether the incidence of accounting irregularities correlated with the firm-level climate change exposure and whether climate change is a factor that leads to financial reporting failures.

2.2 Testable predictions: The Effect of Climate Change Exposure on Misreporting

We use fraud triangle model to formalize the intuition that motivates our predictions.

2.2.1 Opportunity Channel

Firm-level climate change might lead to more misreporting behavior. According to the FASB (2010, CON2-6), comparability is defined as "quality of information that enables users to identify similarities and differences between two sets of economic phenomena". Climate change can inevitably detriment accounting comparability stemming from the professional judgment in accounting treatment arising from climate exposure, especially since accounting standards such as IFRS and GAAP do not refer explicitly to climate-related matters. Climate-related opportunities and risks might exert influence on management's critical forward-looking assumptions, estimates, and judgments, thereby contributing to increased estimation uncertainty (Müller et al., 2024). Firm's financially material climate change exposure affects accounting treatment of accounting elements (asset, liability, income and expense) with potential contracting consequences. For instance, per ASC 360, companies are mandated to perform an annual review of the estimated residual values of non-current asset and must consider climate-related matters in applying GAAP when the effect of those matters is material in the context of the financial statements taken as a whole, introducing a significant degree of complexity and uncertainty. A piece of real estate near the coast may have a different risk profile and useful life compared to one in an inland area due to the risk of rising sea levels or increased storm frequency. This variability makes it difficult to apply a one-size-fits-all approach to asset valuation and life estimation. Alternatively, Per ASC 450, companies might need to recognize new liabilities or adjust the valuation of existing ones to account for environmental remediation costs or penalties for non-compliance with environmental regulations and disclose GHG-related commitment. Given that FASB has not yet made any update to existing accounting standards and not directly addressed specific transactions, there is diversity in practice regarding climate change indicatives, including accounting for carbon reduction and neutrality programs, developing new green technology, financial instruments with ESG-lined features[1]. The accounting for climate related arrangements can often be complex and require judgment and evitable harm accounting comparability.

The reduction in comparability due to climate change can potentially increase the risk of financial misreporting. When financial statements become harder to compare due to varied responses to climate risks, it becomes more challenging for external parties to detect inaccuracies or anomalies (Zhang, 2018). For investors, creditors, and monitors, the decreased comparability complicates the process of evaluating a company's financial health and future performance prospects. High comparability of financial information across firms reduces the marginal costs of information acquisition and processing for investors and specialized monitors (Sohn, 2016). Therefore, investors and specialized monitors are better able to evaluate the company's performance as peer-based comparability enhances the accuracy of valuations when analyzing the business fundamentals of a company (Young and Zeng, 2015). Balakrishnan and Cohen (2011) find that the discipline role of market competition on corporate fraud is more obvious in industries with high level of financial statement comparability. Thus, this is consistent with opportunity component in fraud triangle model that predicts that companies in circumstances with low accounting comparability are more likely to commit fraud.

[1] See https://www.ey.com/content/dam/ey-unified-site/ey-com/en-us/technical/accountinglink/documents/ey-tl14767-221us-07-28-2022.pdf for more details and examples in different accounting consideration for transactions relating to climate change initiatives.

2.2.2 Pressure Channel

From pressure perspective, climate change leads to negative financial and operational performance (see Traore and Foltz 2017; Xie, 2017; Zhang et al., 2018; Li et al., 2021; Somanathan et al. 2021; Pilcher et al., 2002; Sepp ̈anen et al. 2006; Xiang et al. 2014). Investors therefore require higher rate of return and compensation towards firms with high climate change exposure, indicating greater difficulty in obtaining external financing (Ginglinger and Moreau, 2023). Elevated financing costs augment the financial burden on corporations, potentially impeding their ability to meet financial objectives (Pike, Neale and Saeed, 2018). Empirical evidence indicates that the financial pressure experienced by companies exerts a discernible influence on corporate behavior (Nickell and Nicolitsas, 1999). Companies experience heightened pressures, leading them to incline towards the manipulation of financial reporting to present a more robust financial standing, thereby seeking more favourable financing terms for company. Besides, Companies may resort to misreporting to portray a more robust financial position, thereby safeguarding stakeholder confidence and avoiding adverse reactions from shareholders. This can be crucial for maintaining investor trust and preventing a decline in stock prices. In such cases, companies may be more inclined to meet short-term performance objectives and solid market confidence through financial statement misreport than long-term sustainability considerations (Dechow et al., 1996). These pressures align with the 'pressure' or 'motivation' component of the fraud triangle, suggesting that companies under severe financial stress due to climate change may be more inclined to engage in misreporting to appease stakeholders, secure financing, or meet market expectations. The need to maintain capital confidence amid deteriorating financial conditions can push management towards unethical decision-making, including the manipulation of financial statements. Moreover, this underperformance may have consequential implications for the Chief Executive Officer (CEO), potentially jeopardizing their tenure and exposing them to reputational risks. Cooper, Raman, and Yin (2018), have indicated that heightened climate change risk may lead to a tarnished corporate reputation, with the CEO being held accountable. Consequently, Hossain et.al (2023) provide direct empirical evidence demonstrating that CEOs of companies with higher climate change risk earn higher equity-based compensation to compensate for their risk and in line with the compensating wage differential theory. The implementation of equity-based incentive compensation policies aligns the personal interests of management with share price movements and overall financial performance, making managers more concerned about short-term stock prices. It may be in their self-interest to give the appearance of better performance through misreporting given that accounting information used by investors to value stocks, creating an incentive for managers to manipulate earnings (e.g., Armstrong et al., 2013; Cheng and Warfield, 2005; Baber et al., 2007; Harris and Bromiley, 2007). Overall, financial pressures, stemming from underperformance, and self-interest protection will change company's financial reporting behaviour. Whether viewed from the perspective of sustaining confidence in capital markets or the management's imperative to safeguard its own interests, companies may tend to engage more extensively in financial misreporting behaviour.

Collectively, the arguments laid out in this section suggest that company faced high climate change exposure will be more likely to engage in financial reporting irregularities. This expectation is stated formally in H1:

H1: *Climate change exposure is positively associated with the likelihood of misreporting.*

3. Data

3.1 Sample Construction

Our research require data on firm-level climate change exposure, firm performance, and proxies for misreporting. We construct our final sample by collecting financial statement information from Compustat, stock return data from the Center for Research in Security Prices (CRSP), accounting restatements from AuditAnalytics and firm-level climate change exposure from Sautner et al. (2023). For our cross-sectional tests, we also obtain climate change belief data from the Yale Climate Opinions survey in 2023 (the lasted published date). Our final sample is reached by screening for data availability in Compustat, Sautner et al. (2023) (for climate change exposure data) and AuditAnalytics in that order.

After excluding observations that lack necessary firm-year observations to form our baseline model, the final sample consists of 16,303 firm-years (2,990 firms) over the period 2003-2020[2]. The sample began in 2003 as our climate change proxy is not available before 2002 and we measured independent variable one year prior to the evaluation of misreporting. And sample ends in 2020 to allow time for misreporting to be investigated.

3.2 Variable Measurement

3.2.1 Measures of misreporting

To capture intentional misreporting, we follow Hennes et al. (2008) to identify misstatement (i.e., intentional misreporting) from error (i.e., unintentional misapplications of GAAP) and only focus on instances where the misstatement was due to intentional misreporting in which the restatement announcement explicitly mentions the term "fraud" or "irregularity," the SEC publicly disclosed an investigation into the accounting issue, or there is an (non-SEC) independent investigation. For each firm-year observation in our sample, we define a dummy variable, *Misstatement*, equal to 1 if the firm's financial statements (quarterly, annual, or otherwise) are subsequently intentionally misstated, and zero otherwise. In our final sample, after requiring necessary control variables, 212 observations are due to intentional misrepresentations. The primary advantage of using misstatement to proxy misreporting lies in the ability to identify specific cases where financial outcomes were intentional misreported. One limitation to this variable in the current context is that this variable relies on restatements, contingent upon a company's voluntary decision to restate or external pressure from regulatory bodies such as the SEC, thereby potentially omitting instances of misreporting not subjected to restatement Armstrong et al. (2013).

[2] The literature often excludes observations from highly regulated industries such as financial and utility firms. However, climate change impacts all companies irrespective of industry. Utility firms, significant greenhouse gas emitters, are included in financial economic studies relating to climate change, as evidenced by works such as Nguyen and Phan (2020), Bolton and Kacperczyk (2021) and Ginglinger and Moreau (2023).

To assess the robustness of our results to our measurement choices, we also consider several alternative measures of misreporting used in prior literature, we use absolute value of discretional accruals, *Discretion*, as continuous measures with considerable cross-sectional variation (e.g. Petroni and Wang, 2010; Ali and Zhang, 2015). *Discretion* is calculated from each of the three models of Kothari et al. (2005), Dechow and Dichev (2002), McNichols (2002).

3.2.1 Measures of climate change exposure

The key independent variable in our study is the firm-level climate change exposure proposed from Sautner et al. (2023).[3] They builds this measure from the bigram analysis of a firm's quarterly earnings conference. During the past two decades, earnings conference calls have become a primary information channel for firms to convey important messages to capital market participants. Using the keyword discovery algorithm proposed by King et al. (2017) to construct climate change bigrams in identifying climate change conversation in the transcripts of quarterly earning call, climate change exposure metric is then calculated as the total number of climate bigrams scaled by the total number of all bigrams in the transcript:

$$Cimate\ Change\ Exposure_{i,t} = \frac{1}{B_{i,t}} \sum_{b}^{B_{i,t}} (1[b \in \mathbb{C}]),$$

(1)

where b = 1, 2, ..., $B_{i,q}$ are all the bigrams of firm i in quarter q. D(b) is a dummy variable equal to one if bigram b is related to climate change, and zero otherwise. For purposes of exposition, the measures are multiplied by 1000. This measurement suggests the frequency of climate change events as mentioned and discussed in earnings conference calls at firm i in quarter q. Annual measure for each firm is obtained by averaging the quarterly measures.

[3] The data on firm-level climate change exposure is available at https://osf.io/fd6jq/

Climate change exposure captures the attention that firm managers devote to climate change-related topics during market interaction. The primary benefit of using *Climate Change Exposure* is that this measure reflects the soft information exchanged between analysts and managers, which allows this study to extend the scope of management insights beyond those derived from hard information (e.g., carbon emissions and extreme local weather events) (Sautner et al., 2023). Furthermore, this metrics reflect the aggregated perspectives of essential stakeholders regarding a firm's exposure to climate change and are oriented towards future implications.

This climate exposure measurement is arguably a better measure compared to traditional measures employed in many studies, such as natural disaster and carbon emission, for addressing climate-related research question. Conceptually, the concept of climate change is broader than natural disasters, and natural disaster data are often available at the macro level, thereby failing to capture firm-level sensitivity to catastrophic events. Furthermore, data on carbon emissions are limited to firms that voluntarily disclose this information, introducing self-disclosure bias and missing value problems. This measure has already been recognized as effective and has been adopted in many recently published studies (e.g., Hossain et al., 2023; Feng et al., 2024;).

3.4 Model specification

We use the following probit regression model to estimate the effect of climate change on financial misreporting behaviour:

$$Misreporting_t = \alpha + \beta_1 Climate\ Change\ Exposure_{it-1} + \beta_2 Control_{it-1} + \beta_3 Z_{it} + \varepsilon_{it}, \quad (2)$$

where *Misreporting* is the measures of misreporting (*Misstatement*). *Misstatement* equals 1 if company misstated financial statements in the given firm-year, and 0 otherwise. The main independent variable is *climate change exposure* provided by Sautner et al. (2023). We include a vector of control variables from extant misreporting literature (see Burns et al., 2010; Armstrong et al., 2013; Jayaraman and

Milbourn, 2015; Christensen et al., 2018). We control the size effect (*Size*), growth opportunities *(Market to Book)*, leverage (*Leverage*), past accounting performance (*ROA*), capital intensity (*Capital*) and intangible asset (*Intangibles*), inventory (*Inventory)*, receivable (*Receivable*). Also, in light of prior research indicating that the amount of external financing (*Financing*), the size of any acquisitions within the year (*Acquisition*), and interest coverage *(Interest cover)* are significant determinants of financial restatements (Efendi et al., 2007; Burns et al., 2010). Given that firms experiencing financial distress are more susceptible to fraudulent activities (Maksimovic and Titman 1991), we account for this determinant by assigning the variable *Negative Book Equity Indicator* a value of 1 when liabilities exceed assets, and 0 otherwise (Lennox and Pittman, 2010). We also control for the level of sales growth (*sales growth*) as poorly performing (slow-growing) or high-growth firms may commit fraud in order to increase or sustain their sales growth (see Erickson et al. 2006). Consistent with existing literature, all independent variables are measured one year prior to the evaluation of misreporting. All variables are defined in Appendix A.

To address year effects, we consider two alternative approaches. We first incorporate year dummy variables to account for any time effects in financial fraud. We also introduce a time trend variable as the frequency of accounting fraud has been decreasing, particularly since the Sarbanes-Oxley Act (SOX) of 2002 (Nagy, 2010). Because the sample is unmatched, we also include industry fixed effects at the one-digit SIC level following Erickson et al. (2006). All standard errors are clustered at the firm-level.

4. Empirical Results

4.1 Descriptive statistics

The distribution of the sample across year and industries is detailed in Panels B of Table 1. It is noted that the major proportion of the misstatement case comes from the manufacturing sector (28.77%), which is consistent with Jia et al. (2014). Table 2 shows our descriptive statistics for the variable used in our main model. The table contains statistics for our 2003-2020 sample. To mitigate the effect of outlier, all continuous variables are winsorized at the 1% level. Panel A reports descriptive statistics for each measure of misreporting. Panel A shows that 1.3% of our sample had misstated their financial statements. These percentage is slightly lower to those reported by Armstrong et al. (2013) (2.7%) and by Christensen et al. (2018) (2.1%) as their sample includes many misstatement cases from before the implementation of the Sarbanes-Oxley Act (SOX). Panel A also shows that average unsigned discretionary accruals range from 13.069% to 22.177% of total assets, depending on the model. Panel B reports descriptive statistics for the climate change variables. The mean for climate change exposure measure is 0.912 with a median value of 0.28. This suggests that, for a typical firm, approximately 0.09% of the bigrams in earnings conference call transcripts pertain to discussions on climate change-related topics.

In Panel C, we show descriptive statistics for several firm characteristics. The average size of our sample firms is 0.4 billion (exp (5.994)). The average market to book ratio is 2.498, indicating that average firm has potential for future growth. On average, the leverage ratio is 30.3% and the average ROA is -8.7%. In particular, average firm have 6.4% intangibles in total asset and 23.2 % tangible asset in total asset on average.

We also compare the mean values of the climate change variables in the full sample and outcome-matched sample between misstating firm-year and non-misstating firm-year. The results in Panel D of Table2 indicate that misstatement is concentrated in firms with high climate change exposure (t-statistic = 0.621) and more likely by small companies (t-statistics =-0.826). The mean difference between misstated firm-years (N=193) and matched non-misstated firm years (N=193) are also reported in Panel A[4] of Table 6 and the difference remains significant in our matched sample.

4.2 Main regression: Climate change and misreporting

[4] We have 212 misreporting firm-year in our full sample. In the outcome-based matching process, we match each misreporting firm with non-misreporting firm year based on the same year, industry and closest size. We are unable to attain successful matches for 19 misreporting firm year. Please refer to section for a detailed matching procedure.

Table 3 presents evidence on whether the likelihood of accounting fraud varies significantly with different firm-level climate change exposure (Hypothesis 1). We estimate our model by including year and industry dummy variable to control for year and industry effect. We do not control firm fixed effect as firm fixed specification would dummy out all companies that show no variation in the dependent variable across time (Baltagi, 1995; Greene, 2004), causing all of the no-fraud companies to be excluded from the estimation sample. Also, standard errors in our regression are clustered at the firm level and we do not cluster standard errors by year. Because there are too few years in our sample period. Using Monte Carlo simulations, Thompson (2011) shows that clustering on time is appropriate only when there are at least 25 periods.[5]

Our analysis from the probit models based on the full sample suggests the *Climate change exposure* coefficients are positive (θ>0) and statistically significant at the 0.01 level, with the z-statistics ranging from 2.593 (Column 1) to 2.851 (Column 3). The results reinforce the univariate evidence and starkly illustrates that when the firm faces high level of climate change exposure, company has higher likelihood to misreport financial statements. As we achieve these conclusion in both univariate and multivariate specifications, our conclusions are less likely to be influenced by whether specific controls are included or excluded (Jayaraman and Milbourn, 2015).

Also, the directions of our control variables align with those observed in previous research (e.g. a negative sign on the firm size, a negative sign of capital). It is worth noting that the coefficient of *Time Trend* is negative and statistically significant in our Column (3), which supports the findings that SOX have contributed to higher quality of financial reporting and lower fraud instances after 2002 (Karpoff et al., 2008).

4.3 Mechanism Analysis

5 We cluster standard errors by firm and year in robustness check, the coefficient on main variables remains statistically significant at the 1-percent level

Our work has demonstrated a positive association between a firm's exposure to climate change and tendency to misreport financial report. This subsection is built on fraud triangle framework to investigate whether the opportunity channel and the pressure channel serve as the mechanisms through which climate change increases the likelihood of misreporting.

4.3.1 Opportunity Channel

Regarding the opportunity channel, H2 proposes that climate change create window for broader professional judgement application and decrease the accounting comparability, which provides opportunities for misreporting behaviour. Our models testing whether climate change weaken accounting comparability have the following form:

$$Comparability_{it} = \alpha + \beta_1 Climate\ Change\ Exposure_{it} + \beta_2 Control_{it} + \beta_3 Z_{it} + \varepsilon_{it} \quad (3)$$

When the effect of climate-related matters is material in the financial statements, the company must consider these issues. Information about how management has considered climate-related matters in preparing the company's financial statements may be material with respect to the most significant judgments and estimates because GAAP do not explicitly refer to climate-related matters. We first examine whether firms subject to higher climate change exposure decrease accounting comparability due to high subjectivity. We closely follow De Franco et al. (2011) to measure accounting comparability, in which firms whose economic events are correlated will have correlated financial statements over time when their accounting is similar. Details of the calculation procedure can be found in Appendix. We include a vector of controls used in our baseline regression to remain consistent, and Z_{it} is a vector of fixed effects. We control for year fixed effects to consider that convergence in firm-specific earnings multiples over the period (see Land and Lang, 2002), for industry fixed effects (as accounting flexibility varies across sectors) and firm fixed effects to control for time-invariant firm characteristics.

Panel A, Table 8 presents our results. In columns (1), we include all the observations with non-missing value. By excluding zero exposure data (Table 8, columns 2 and 3) and replicate our equation 3, we verify the results are robust. The findings support that climate change exposure is significant negatively correlated with accounting comparability and our results are qualitatively unchanged.

4.3.2 Pressure Channel

To test whether pressure channel is involved, we focus on whether firms with high climate change exposure are subject to higher operating uncertainty. To response to climate change, if firms are under deteriorating financial conditions, company tend to misreport financial results to solid market confidence. We focus on the impact of climate change exposure on the operating uncertainty. For these regressions, we adopt pooled ordinary least squares (OLS) regressions with industry-year fixed effects in Equation (4) and Equation (5). the equation is as follows:

$$\frac{operating\ cash\ flow_{it}}{asset_{it-1}} = \alpha + \beta_1 Climate\ Change\ Exposure_{it} + \beta_2 Control_{it} + \beta_3 Z_{it} + \varepsilon_{it} \quad (4)$$

$$\frac{revenue_{it}}{asset_{it-1}} = \alpha + \beta_1 Climate\ Change\ Exposure_{it} + \beta_2 Control_{it} + \beta_3 Z_{it} + \varepsilon_{it} \quad (5)$$

We use Altman's Z-score (Altman, 1968) as a measure of bankruptcy risk. *Bankruptcy risk* is a dummy variable with value equal to one if Z-score is smaller than 1.8 and zero if Z-score is larger than 3. To estimate the effect of climate change exposure on the likelihood of default, following probit model is outlined:

$$Bankrupcy\ risk_{it} = \alpha + \beta_1 Climate\ Change\ Exposure_{it} + \beta_2 Control_{it} + \beta_3 Z_{it} + \varepsilon_{it} \quad (6)$$

$Climate\ Change\ Exposure_{it}$ refers to the combined views of key stakeholders about a firm's climate change exposure, $Control_{it}$ in Equation (4) – Equation (6) is a vector of controls in our equation (1) to remain consistent and Z_{it} is an industry–year fixed effect, absorbs the variation in financial performance resulting from technological change or industry-specific economic trends.

In Table 8, Pabel B, we show the estimates of the effect of climate change on financial performance and operating uncertainty. We find that one standard deviation increase in climate change exposure generates a 0.294% decrease (1.117*0.263=0.294, with 1.117 being the standard deviation of the Climate change exposure within this sample) in the operating cash flow generating ability (column 1) and a 2.129% decrease in revenue generating ability (column 2). We also observe that the likelihood of bankruptcy increased with higher climate change exposure. Our findings are consistent with the related literatures (e.g., Feng et al., 2024; Pankratz et al., 2023).

Overall, our results suggest that climate change exposure put pressure on companies's operation by leading to cash flow shortfall, weaker revenue generating capacity and higher financial distress. These pressures align with the 'pressure' or 'motivation' component of the fraud triangle, suggesting that management or other employees have an incentive or are under pressure, which provides a reason to commit fraud (AICPA, 2002, Para. 7). Companies under severe financial stress due to climate change are more inclined to engage in misreporting to appease stakeholders, secure financing, or meet market expectations (Wang et al., 2010). The need to maintain capital confidence amid deteriorating financial conditions can push management towards unethical decision-making, including the manipulation of financial statements.

5. Robustness Checks

5.1 Alternative research design

Table 5 follows several research designs referenced in prior studies to prove the robustness of our findings. We rerun our main tests using probit model without year- industry fixed effect and standard errors are clustered by firm and year, following the model proposed by Armstrong et al. (2013). Column 1 reports our results and confirm previous findings at 5% level, which address potential issues of correlated residuals within the same firm over time or across different firms within the same year and confirm our results are not affected by fixed effects included. Model in Column (2) incorporates a random effects probit regression to account for unobservable firm characteristics, aligning with the approach by Lennox and Pittman (2010). This model supports that the coefficient for the climate change is significantly positive at the 10% level of significance. Model in Column (3), following the model specification of Erickson et al. (2006), utilizes a logistic regression, which also supports the persistence of our results at the 1% level. We also test linear probability model (LPM) because LPM model does not impose potential bias or inconsistency on the coefficients and standard errors (Greene, 2004)[6]. Again, our findings remain robust with a significantly positive coefficient at the 10% level. The consistent results across different designs (columns 1-4) reduces the likelihood that the climate change merely reflects some unaccounted firm-specific characteristics that could otherwise explain fraud cross-sectionally.

5.2 Alternative misreporting measurement

We also use alternative measurement for misreporting behaviour to mitigate the potential measurement error in our proxy for misreporting behaviour. We construct discretional accruals, *Discretion*, as the absolute value of discretional accruals calculated from following three literature: Kothari et al. (2005); McNichols (2002); Dechow and Dichev (2002). Discretionary accruals are calculated as the residual, or unexpected, accruals from each of these three models. Using these continuous measurements, we could observe considerable degree of variation. The findings in Table 6 shows consistent significance in the relationship between climate change and misreporting behaviour (significant at the 1% level when proxy as *Discretion_Kothari* and at the 5% level when proxy as *Discretion_McNichols* and *Discretion_ Dechow and Dichev*).

5.3 Sensitivity Test

[6] The use of a linear probability model for dichotomous outcome variables is supported by Angrist (2009) and is widely used in contemporary research (e.g., Hanlon and Hoopes (2014), Christensen et al. (2018)). This model is favoured for its simplicity and ease of interpretation.

We also perform sensitivity test: (1) excluding firms from financial industries (SIC code: 60-69) (leaving out 3,367 observations); (2) excluding firms from utilities industries (SIC code: 40-49) (leaving out 1,396 observations); (3) excluding firms from financial and utilities firms (SIC code: 60-69 and SIC code: 40-49)(leaving out 4,763 observations); (4) excluding or controlling for time periods influenced by the global financial crisis (Fiscal year: 2008-2009) (leaving out 2,100 observations); (5) excluding or controlling the COVID-19 pandemic period (Fiscal year: 2020) (leaving out 823 observations); (6) excluding firms that have zero climate change exposure (leaving out 3,478 observations); (7) winsorizing all continuous variables at the 5st and 95th percentiles to control for outliers. None of these variations changes our conclusion (See Appendix).

5.4 Matching sample regression

5.4.1 Outcome-based matching sample test

In addition to our primary regression tests using misreporting firm years and all non-misreporting firm years with required data, we also investigate the relation between climate change and misreporting behaviour by constructing outcome-based matched sample. Following matching procedure in Erickson et al. (2006) and Efendi et al. (2007), we match each 212 fraud firms to a non-fraud firms based on industry (two-digit Standard Industrial Classification [SIC] code), year, and firm size (total assets). We have 193 fraud firms and 193 non-fraud firms in the matched sample tests[7].

We then test for differences in climate change exposure between the misreporting sample and the matched sample. Panel A of Table 6 reports the univariate results, indicating that misreporting firms have significantly higher mean levels of climate change exposure (p-values of 0.000). Multivariate evidence on the misreporting behaviour using Equation (1), specifications proposed by Armstrong et al. (2013) and specifications proposed by Christensen et al. (2018) are presented in panel B of Table 8. We

[7] In our data processing, 19 misreporting firm year could not be matched with non-misreporting firm years from the same industry, year and the closest asset value.

observe that the coefficients on climate change exposure are positive and statistically significant. These results reinforce our evidence in Table 3 that company with higher climate change exposure is associated with a high incidence of misreporting.

5.4.2 Entropy Balance

To address potential biases arising from non-identically distributed covariates, this study employs the entropy balancing method proposed by Hainmueller (2012). Hainmueller (2012)'s method apply optimally-chosen weights as a function of the statistic distributions in both the treatment and reweighted control groups (Imai and Ratkovic, 2014). An advantage of this method is that it achieve convergence in covariates between the treatment group and control groups, thereby ruling out the possibility that differences in outcome may be attributed to nonparametric variations in the observables' moments (Egger and Tarlea, 2021). Another advantage is that this method uses all available data and avoids discarding unmatched observations. Applying the code developed by Hainmueller and Xu (2013), our sample is balanced at the first, second, and third moments of the covariates. The treatment variables are based on climate change exposure. A firm is considered to belong to the treated group (control group) if its climate change exposure is above (below) the 60th (40th) percentile within its one-digit industry classification.

Panel B, Table 6 reports the results for the outcome-based sample with misstatements as dependent variables (column (1)) and discretions as dependent variables (column (2)). Overall, these results using entropy balancing approach confirm the patterns observed in our baseline tests (Table 3) that companies tend to misreport financial statements when their exposure to climate change is higher.

5.4.3 Propensity Score Matching Approach

We then examine the relation between climate change and misreporting using propensity score matching procedures, as described in Lennox and Pittman (2010), to control for differences in the nature of high climate exposure group (treatment group) and low climate exposure group (control group). Specifically, we first estimate the propensity score as a function of 13 control variables[8] that predicts whether the company is facing high or low climate change exposure. Each high climate change exposure firm is then matched to a low climate change firm that has the closest propensity score. We then assess the success of the results by testing for covariate balance between high climate change exposure group and low climate change exposure. Appendix shows the mean value and *p*-values of firm characteristics from *t*-test in the propensity score matched sample. The matching is successful.

We defined treatment variables based on climate change exposure. A firm is considered to belong to the treatment group if the climate change exposure has a value above the 50th percentile either for the total sample (columns (1) and Columns (5)) or at the one-digit industry level ((Columns (2) and Columns (6)). We also define the high (low) climate exposure group if the climate change exposure has a value above (below) 60th (40th) percentile for the total sample (Columns (3) and Columns (7)) and at the one-digit industry level (Columns (4) and Columns (8)). We conduct tests on misstatement (Columns (1) to Columns (4)) and discretional earning management (Columns (5) to Columns (8)). Our results for the propensity-score matched-sample are reported in Panel C, Table 6. All regressions include firm control as baseline regressions and year-industry fixed effects. We find that coefficients in all columns is statistically significant at the 1 percent level or the 5 percent level, indicating that any variation in misreporting behaviour is attributable to differences in climate change exposure rather than differences in other characteristics. Our conclusion that companies with higher levels of climate change exposure are more likely to misreport their financial statements again hold.

6. Subsample analysis

[8] We include the union of all control variables used in our baseline regression.

To enhance the robustness of causal inference and eliminate potential alternative explanations, this section applies the cross-sectional variation such as asset tangibility, firm size, environment risk, equity issue, market leverage and worriedness about global warming. These tests provide further empirical support for the mechanisms of the opportunity channel and pressure channels previously discussed.

6.1 Asset Tangibility

Asset tangibility enables firms to adapt more professional judgment (opportunity channel) and increases their vulnerability to the impacts of climate events (pressure channel). Per ASC 330, firms may recognize loss by write down inventory value to the lower of cost and market when floods, hurricanes, droughts, and other extreme weather events directly damage inventory. Estimates of utility on the inventory date are based on management's judgement exercised (FASB, ASC 330-10-35-4). This opens opportunity to commit financial fraud through estimation of utility of inventory. Decrease in closing inventory rises the cost of goods sold and therefore decrease profitability (Pong and Mitchell, 2012). This put pressure on financial performance. Moreover, firms with higher asset tangibility encounter more frequent impairment test triggered by climate-related matter. For example, rising temperatures might require earlier equipment replacement and equipment with high pollution suffers from dropped market value. Per ASC 360, impairment loss needs to be recognized if the carrying amount is greater than the undiscounted cash flows and fair value. Future cash flow estimation includes entity's own assumptions and are based on manager's understanding relating to all available evidence (FASB, ASC 360-10-35-30). This situation also provides an opportunity for financial manipulation through the subjective estimation of future cash flows. These impairment loss results in operational disruption, reduced profitability and cash flow concerns, imposing pressure for firms with substantial physical asset. Overall, the incorporation of climate change considerations has expanded the scope of managerial professional judgment in companies possessing tangible assets, providing these firms with increased opportunities to engage in financial fraud. Additionally, firms with high asset tangibility often experience worsen performance and greater operating uncertainty, thereby facing greater pressure.

Hence, we first investigate the cross-sectional heterogeneity in asset tangibility and predict that the effect of climate change exposure on misreporting behaviour is more prominent when asset tangibility is high. To test this conjunction, we construct subsamples based on tangibility as proposed by Berger et al. (1996) in Columns (1) and (2). A firm year observation is defined as high (low) tangibility if the value of *Tangibility_Berger* is above (below) the sample median. We also use the proportion of intangible asset to separate group in Columns (3) and (4). High (low) intangible proportion in total asset suggests low (high) asset tangibility. When we rerun our baseline regression using subsample groups, we observe this relationship is only positive and statistically significant for high tangibility group for both of our tangibility proxy. We present these findings in Panel A of Table 9. Taken together, these results are consistent with the view that firms with more exposure to climate change have more opportunities to exercise accounting discretion, potentially leading to misreporting, and are under higher pressure in managing their financial reporting.

6.2 Firm Size

It is argued that the positive association between climate change and accounting irregulates should be more prominent in small firms since firms in big size attract more public scrutiny (Udayasankar, 2008). Curtis et al., (2019) document that large firm have more employees to potentially serve as whistleblowers. Wilde (2017) empirically find that whistleblowing can plays a deterrent role in curbing subsequent financial misreporting behaviour. Furthermore, larger companies are more inclined to implement environmental management practices, because they typically possess more extensive resources (Bansal, 2005). This includes financial resources for ESG data disclosure, investing in sustainable technologies, diversifying energy sources, and implementing more resilient supply chain practices under resource-based view proposed by Barney (1991). Also, larger firms might have more instruments devoted to understanding and managing sustainable behaviour (Graafland et al., 2004) and more knowledge of sustainability management tools (e.g., environmental management systems or sustainability balanced scorecards) compared to small firms (Hörisch et al., 2015), enabling them to adapt more swiftly and effectively to changing environmental conditions. This capacity to mitigate the effects of climate change could lessen the financial pressures that might lead larger firms to misreport.

Therefore, this cross-sectional analysis categorizes the sample based on firm size. Baseline regressions are estimated separately for each subsample. Firm size is defined as the natural logarithm of total assets. A firm-year observation is allocated to the large corporations' group if its firm size exceeds the sample median, and to the small firms group if its value falls below the sample median. The findings from this subsample analysis are presented in Panel B of Table 9. The positive and significant impact on misreporting behaviour is observed only in groups of smaller corporations. This result, therefore, indicates that the impact of climate change exposure on misreporting behaviour is stronger in smaller-sized companies as these firms received less monitoring, and they face higher pressure from climate change issues.

6.3 Environmental litigation risk firms

Environment litigation risk exposure is likely to play a moderating role in our study. Firms with high environmental litigation risk are subject to increased environmental liabilities due to the nature of their line of business and industry. Prior literature has discussed the direct effect of environmental liability on firms' performance and risk profile. Specifically, environmental liabilities are legally enforceable obligations that may lead to significant and continuing economic benefit outflows (Chang et al., 2018). Such liability increases the risk of bankruptcy (Schneider, 2011) and business risk faced by firms (Chang et al., 2018). This situation leads to firms with high environmental litigation risk enduring increased pressures given that those firms are more easily and frequently recognition of environmental liabilities. Through pressure channel, such firms are more susceptible to engaging in financial fraud. However, on the other hand, with the rising awareness of climate change and environmental concerns, firms in high environmental litigation risk industries received more monitoring and scrutiny from capital market as investor are concern more about their loss stemming from environmental litigation risk. Curtis et al., (2019) posts that firms operating in a regulated industry face additional scrutiny. Moreover, high litigation risk create incentives for companies to implement proactive environmental initiatives or preempt more stringent environmental regulations and enforcement (Wu et al., 2024). Companies active management of environmental risks may result in increased environmental initiatives, less business risks, higher stock return, a greener reputation (e.g., Chiu et al., 2017; Kim et al., 2015; King and Lenox, 2001). A higher natural susceptibility of high environmental risk could thus be perceived as an monitoring and governance role and have a deterrent effect on companies' behavior and make them more transparent. Therefore, we use subsample regression to investigate the moderating role of environmental litigation risk in the relationship between climate change and misreporting behaviour.

We separate our sample into high and low environmental litigation risk subgroups. Consistent with Fard et al. (2020), firms with high environmental litigation risk are defined as those in given industries (2-digit SIC codes: 49, 28, 29, 37, 13, 36, 35, 33, 38, 26 and 10) based on environmental litigation cases from 1980 to 2016 in the US, obtained from Audit Analytics[9]. Our results are shown in Panel C, Table 9. The cross-sectional analysis proves that our results are predominantly driven by firms in industries with low environmental litigation risk. For such firms, the coefficient is positive and highly significant, whereas for firms in high litigation risk industries, the coefficient is insignificant.

[9] A full list of industries (SIC) with the highest and lowest environmental litigation cases from 1980 to 2016 in the U.S. can be found in Fard et al. (2020).

6.4 Equity Issue Status

We then examine the moderating role of share issuance in the relationship between climate change and financial fraud because equity issuance both alleviates financial constraints and increases public scrutiny. Debt and equity are the two main securities companies use to obtain capital (Kopcke et al., 1989). If these companies issue fewer shares in a given year, they might struggle to fund large-scale environmental projects, thereby facing intensified financial constraints. In response, through a pressure channel, companies might be more inclined to misreport financial results to mask these difficulties and maintain investor confidence. On the other hand, issuing shares can increase a company's financial slack, providing more resources to address unexpected challenges posed by climate change. This financial flexibility can reduce the need to resort to misreporting as a way to manage external pressures or to meet short-term financial targets (Byoun, 2011). From the view of monitoring effect, issuing shares also leads to increased scrutiny from investors, analysts, and the media. This increased visibility can act as a deterrent against financial misreporting as the likelihood of detection increases (Ferri et al., 2018), and it encourages companies to maintain transparent and accurate reporting practices to sustain their reputation and investor trust.

We examine the moderating role of equity issue by estimating our baseline regression for each subsample. An observation is categorized into the high (low) equity issue group if its equity issued value is above (below) the sample median. The results are summarized in Panel D, Table 9. As shown, the coefficient on climate change exposure is positive and significant at the 1% level for the low equity issuance group. However, the effect of climate change is statistically non-significant for the high equity issuance group. This finding aligns with expectations, indicating that the positive impact of climate change exposure on misreporting behaviour is more pronounced for low equity issuance firms.

6.5 Market Leverage Status

We next test if the market leverage level moderates the relationship between climate change and financial misconduct. If a firm has high market leverage level, company face greater financial pressure as they need to ensure steady cash flows to meet interest payments and repay principal amounts. In align with our pressure channel hypothesis, misreporting financial results can be applied to temporarily alleviate concerns from creditor and investors about the company's ability to repay its debt, particularly under uncertain and challenging conditions caused by climate impacts. In addition, lenders impose debt covenants to curtail managerial actions when their interests are at risk (Christensen and Nikolaev, 2012). Laux (2022) posits that managers are motivated to engage in misreporting to circumvent covenant breaches and maintain control rights. Pittman and Zhao (2020) concludes constraints imposed by debt covenants can prompt accounting decisions that encompass GAAP-violating accounting treatments.

Panel E of Table 9 displays the cross-sectional analysis by market leverage level. Companies' market leverage level above the median of the sample are classified as high market leverage, otherwise as low market leverage. The estimated coefficients for climate change are positive and statistically significant at the 1% level for companies classified as high market leverage firms, while they are insignificant for those with low market leverage. These findings suggest that the positive relationship between climate change and financial misconduct is influenced by the firms' market leverage level.

6.6 Climate Change beliefs

The local attitude of a firm's headquarters significantly influences the organizational culture, as employees frequently interact with and are shaped by the prevailing local attitudes of their immediate environment ((Cialdini and Goldstein, 2004). Recent research has found that corporate culture affects a company's strategy and decision-making (e.g., Davidson et al., 2015; Graham et al., 2013; Kumar et al., 2011). In particular, some prior studies imply the effect of local culture on accounting irregularities. For example, McGuire et al., (2012) suggest that firms headquartered in areas with strong religious social norms experience lower incidences of financial reporting irregularities. And Christensen et al. (2018) find that in regions where gambling is more socially accepted, managers are more inclined to engage in financial misreporting practices. Building on this literature, we examine the moderating role of climate change beliefs in the relationship between climate change and misreporting behaviour.

In areas where public awareness and concern regarding climate change are low, there might be a corresponding decrease in demand for environmental accountability and financial transparency, making corporations perceive low opposition when engaging in financial discrepancies because local citizens are less likely to view financial fraud behaviour as unethical in light of the circumstances. This allows these companies potentially to obscure the financial results without immediate reputational damage. Furthermore, there might be less external monitoring of companies with high climate change exposure to adhere strictly to environmental and reporting standards in local areas, providing firms less probability to be detected. Collectively, the arguments laid out in this section lead to our hypothesis that the higher probabilities of fraudulent reporting in firms with higher climate change exposure are more pronounced in areas where the headquarters has low climate change beliefs.

We use the Yale Climate Opinions survey from 2023 to measure climate change beliefs (Howe et al., 2015) and focus on the metric indicating the percentage of a county's citizen that perceives global warming is happening. To include beliefs into our analysis, we have developed an indicator that has a value of 1 if the percentage of people living in the state where the company is headquartered who believe that global warming is happening is higher than the national average percentage. Our cross-sectional results are shown in Panel F of Table 9. The estimated coefficients on climate change are positive and statistically significant at the 1% level for companies headquartered in regions where local citizens have low climate change beliefs, whereas they are insignificant for those in regions with high climate change concern. Our results prove that the positive relationship between climate change exposure and financial misreporting behaviour is moderated by local climate attitudes.

7. Conclusion

A large body of prior literature investigates the economic effect of climate change. However, whether and how climate change affects a company’s misreporting behaviour is still an open question. This study fills this gap by examining whether variation in climate change exposure helps explain the occurrence of financial misreporting. Because climate-related matters may exert influence on management's critical forward-looking assumptions, estimates, and judgments, thereby contributing to increased estimation uncertainty (Müller et al., 2024), this has the potential to decrease accounting comparability and therefore provide opportunities for accounting irregularities. Also, firms with high climate change exposure might confront higher operating uncertainty. Exposure to climate change can result in more extensive damage to firm assets and supply chains, therefore reducing the capacity to generate cash flows and revenue. Pressure can motivate a company to misreport to safeguard stakeholder confidence and avoid adverse reactions from shareholders. Our results show that firms with high climate change exposure are indeed more likely to restate their financial statements due to intentional misstatements. These findings survive all our robustness tests. Consistent with fraud triangle theory, we empirically prove climate change exposure has an adverse impact on accounting comparability (opportunity channel) and leads to greater operating uncertainty (pressure channel). In addition, we consider six settings where the opportunity or pressure to misreport should be greater when (i) the firm has higher asset tangibility, (ii) the firm has smaller size, (iii) the firm is in an industry with lower environmental litigation risk, (iv) the firm has issued few shares in a given fiscal year, (v) the firm has higher market leverage, (vi) the firm is headquartered in areas with lower awareness of climate change. Our subsample analysis suggests the relationship between climate change and misreporting behaviour is more prominent when a company has more opportunity in applying professional judgement and face higher pressure in managing operating performance.

Overall, our research reveals that firms with higher climate change exposure are more likely to misreport their financial statements. The underlying mechanism is reduced accounting comparability (opportunity channel) and increased operating uncertainty (pressure channel). These findings suggest that climate change exposure plays a role in whether firms misreport. To the best of our knowledge, this study is the first that examines how a company's exposure to climate change issues affects the likelihood of misreporting and highlights the need for accounting standard-setting committees to regulate and specify accounting treatment for climate change-related matters.

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Appendix A: Variable Definition

Panel A: Dependent Variable	
Misstatement	A dummy variable which equals one if financial results for that year were intentional misstated and zero otherwise. We consider only restatements related to fraud, misrepresentation, or an investigation by the SEC and PCAOB and follow Hennes et al. (2008)'s procedure to identify misstatements from error in a large sample of restatement obtained from AuditAnalytics.
Discretion	The absolute value of discretionary accruals expressed as a percentage of total assets, calculated from one of three models of accruals. The models considered are (1) Kothari (2006) (2) Dechow and Dichev (2002), and (3) McNichols (2002).

Panel B: Independent Variable	
Climate change exposure	Firm-level climate risk as calculated in Sautner et al. (2023).This measurement is constructed by averaging the quarterly measures of the total number of climate change-related bigrams, normalized by the total number of all bigrams present in the quarterly earnings conference call transcript and then multiplied by 1000.

Panel C: Control Variable	
Size	Natural logarithm of total assets (USD m) (Compustat variable: AT)
Market to Book	Market value of assets (Compustat variables: PRCC_F × CSHO + LT) divided by book value of assets (Compustat variable: AT)
Leverage	Book value of debt (Compustat variables: DLC + DLTT) divided by book value of assets (Compustat variable: AT).
ROA	Earning before interest and tax (Compustat variable: EBIT) divided by total assets at the begining of the year (Compustat variable: AT).
Intangibles	Ratio of research and development (Compustat variable: XRD) and advertising expense (Compustat variable: XAD) devided by book value of assets (Compustat variable: AT).
Capital	Net plant, property, and equipment (Compustat: PPENT) devided by book value of assets (Compustat variable: AT).
Sales Growth	Sales (Compustat variable: SALE) in the current year minus sales in the previous year, divided by sales in the previous year.
Acquisition	Indicator variable for whether an acquisition accounts (Compustat: aqc for 20% or more of book value of asset (Compustat variable: AT).
Loss	Dummy variable equals 1 if net income (COMPUSTAT: NI) is negative, and 0 otherwise
Interest cover	Ratio of interest expense (Compustat: XINT) to net income (Compustat: IB). If net income for the year is negative or interest expense is more than twice net income, Interestcover is set to 2.
Financing	Amount raised from stock (Compustat: SSTK) and debt issuances during the year (Compustat: DLTIS) divided by total book value of assets (Compustat: AT)
Receivable	Accounts receivable (Compustat: RECT) divided by total book value of assets (Compustat: AT)
Inventory	Inventory (Compustat: INVT) divided by total assets (Compustat: AT).
Negative book equity indicator	Dummy Variable equals to 1 if total liabilities (Compustat: LT) exceed total assets (Compustat: AT), and 0 otherwise.
Cash Flow Volitility	Standard deviation of scaled cash flow from operating activities. Cash flow from operating activities (Compustat variable: Oancf) are scaled by total assets (Compustat variable: AT). Standard deviation is measured over years $t - 4$ to t, where year t is the current year.
Sales Volatility	

	Standard deviation of scaled sales. Sales (Compustat variable: SALE) are scaled by total assets (Compustat variable: AT). Standard deviation is measured over years t − 4 to t, where year t is the current year.
Debt Issue	Total liabilities (Compustat variable: LT) in the current year minus total liabilities in the previous year, divided by total liabilities in the previous year.
Equity Issue	Ratio of equity issued (Compustat: SSTK) to book value of equity (Compustat: CEQ)
Dividend	Total dividend (Compustat: DVT) divided by total asset (Compustat: AT)
M&A Indicator	Dummy Variable equals to1 if the company had an acquisition that contributed to sales (Compustat: AQS, 0 otherwise).
Panel D: Other Variables	
Accounting Comparability	Accounting comparability, a firm-year measure following De Franco et al. (2011).
Cash Flow	Cash flow from operating activities (Compustat: OANCF) divided by total asset at the begaininng of year (Compustat: AT)
Revenue	sales (Compustat: SALE) divided by total asset at the begaininng of year (Compustat: AT)
Insolvency Risk	Insolvency risk, a firm year measure following Altman (1968).
Market Leverage	Long-term debt divided by the sum of the year-end market capitalization and the difference between book asset value and common/ordinary equity: DLTT/(AT-CEQ + PRCCD × CHOC) in Compustat.

Table 1: Sample Selection and Distribution

This table shows our sample selection procedure and sample distribution by firm and year. We identify misstatement from restatement in Audit Analytics following the procedure in Hennes et al. (2008). Climate change exposure are provided by Sautner et al. (2023). Our sample consists of 212 fraud firm-year.

Panel A: Sample Selection Procedure

Sampling Procedure	Observations
Total firm-years available on Compustat from 2003 through 2020	156,964
Less:	
Firm-year with missing required climate change data	(135,145)
Firm-years with missing required Compustat financial statement data	(5,516)
Final sample	16,303

Panel B: Composition of Sample by Year and Industry

sample by year					
year	Misreported firm year	%	Non-misreporting firm year	%	Total
2003	16	7.55%	709	4.41%	725
2004	17	8.02%	809	5.03%	826
2005	24	11.32%	859	5.34%	883
2006	25	11.79%	949	5.90%	974
2007	20	9.43%	976	6.07%	996
2008	16	7.55%	1,029	6.39%	1045
2009	17	8.02%	1,038	6.45%	1055
2010	18	8.49%	974	6.05%	992
2011	11	5.19%	928	5.77%	939
2012	15	7.08%	928	5.77%	943
2013	13	6.13%	907	5.64%	920
2014	8	3.77%	815	5.06%	823
2015	4	1.89%	927	5.76%	931
2016	2	0.94%	930	5.78%	932
2017	3	1.42%	828	5.15%	831
2018	1	0.47%	843	5.24%	844
2019	0	0.00%	821	5.10%	821
2020	2	0.94%	821	5.10%	823
Total	212	100.0%	16091	100.00%	16303

Sample by Industry					
Industry	Misreported firm year		Non-misreporting firm year		Total
Agriculture, Forestry, and Fishing	5	2.36%	52	0.32%	57
Mining	11	5.19%	1500	9.32%	1,511
Construction	23	10.85%	2471	15.36%	2,494
Manufacturing	61	28.77%	3333	20.71%	3,394
Transportation, Communications, Electric, Gas, and Sanitary Services	7	3.30%	1389	8.63%	1,396
Wholesale Trade	32	15.09%	1411	8.77%	1,443
Retail Trade	32	15.09%	3335	20.73%	3,367
Finance, Insurance, and Real Estate	30	14.15%	1979	12.30%	2,009
Services	7	3.30%	465	2.89%	472
Public Administration	4	1.89%	156	0.97%	160
	212	100.00%	16091	100.00%	16,303

Table2： Descriptive statistics

This table presents descriptive statistics for firms in our sample. Our sample is constructed from the intersection of Sautner et al. (2023) (Climate change exposure), CRSP/Compustat (accounting and stock price data) and AuditAnalytics (data on restatements) for the time period 2002 to 2020 and covers a total of 16303 firm-years (2,990 firms). Panel A reports descriptive statistics for measures of misreporting. Panel B reports the distribution of the climate change variables used in our analysis. Panel C reports descriptive statistics for selected firm characteristics. All variables are as defined in Appendix 1.

Panel A: Measures of misreporting

Variable	*N*	*Mean*	*Std*	*25th*	*Median*	*75th*
Misstatement	16303	0.013	0.113	0.000	0.000	0.000
Discretion(Kothari)	11106	13.069	21.701	2.767	6.584	13.866
Discretion(McNichols)	11106	20.847	40.776	3.339	8.728	20.162
Discretion (Dechow and Dichev)	11106	22.177	42.707	4.321	10.576	21.881

Panel B: Measure of Climate change

Variable	*N*	*Mean*	*Std*	*25th*	*Median*	*75th*
Climate change exposure	16303	0.912	2.090	0.088	0.280	0.715

Panel C: Firm characteristic

Variable	*N*	*Mean*	*Std*	*25th*	*Median*	*75th*
Size	16303	5.994	2.773	4.153	6.124	7.795
Market to Book	16303	2.498	4.953	1.018	1.332	2.206
Leverage	16303	0.303	0.581	0.030	0.181	0.372
ROA	16303	-0.087	0.655	-0.033	0.037	0.102
Intangibles	16303	0.064	0.149	0.000	0.002	0.060
Capital	16303	0.232	0.266	0.026	0.113	0.361
Sales Growth	16303	0.223	1.093	-0.055	0.061	0.212
Inventory	16303	0.083	0.126	0.000	0.019	0.121
Negative equity indicator	16303	0.083	0.276	0.000	0.000	0.000
Receivable	16303	0.190	0.210	0.045	0.116	0.238
Financing	16303	0.174	0.336	0.002	0.033	0.194
Interest cover	16303	0.976	0.906	0.057	0.579	2.000
Acquisition	16303	0.024	0.155	0.000	0.000	0.000
Cashflow Volatility	11106	0.262	0.960	0.024	0.052	0.124
Sales Volatility	11106	0.186	0.300	0.040	0.096	0.204
Cash Holding	11106	0.236	0.255	0.040	0.135	0.349
Debt Issue	11106	0.329	1.189	-0.073	0.052	0.282
Equity Issue	11106	0.128	0.496	0.000	0.005	0.044
Dividend	11106	0.017	0.051	0.000	0.000	0.012
M&A Indicator	11106	0.075	0.263	0.000	0.000	0.000
Cash Flow	16240	1.539	19.545	-0.691	5.389	12.272
Revenue	16391	88.294	95.009	20.504	63.164	121.737
Insolvency Risk	10866	0.512	0.500	0.000	1.000	1.000

Panel D: Comparison of means for misreport and non-misreport firm-years

Variables	Misstatement=1 (N=212)	Misstatement=0 (N=16091)	Difference in Means
Climate change exposure	1.525	0.904	0.621***
Size	5.179	6.005	-0.826***
Market to Book	2.526	2.498	0.028
Leverage	0.291	0.303	-0.012
ROA	-0.047	-0.088	0.041
Intangibles	0.075	0.064	0.011
Capital	0.16	0.233	-0.073***
Sales Growth	0.292	0.222	0.07
Inventory	0.126	0.082	0.044***
Negative book equity indicator	0.075	0.083	-0.008
Receivable	0.218	0.19	0.028***
Financing	0.172	0.174	-0.002
Interest cover	0.91	0.977	-0.067
Acquisition	0.033	0.024	0.009

Table 3: Baseline Regression: Climate change exposure and Misstatement

This table presents results from estimating a probit model of the likelihood of an accounting misstatement (*Misstatement*) as a function of climate change exposure and control variables. *Misstatement* is a dummy variable which equals one if financial results for that year were intentional misstated and zero otherwise. *Climate change exposure* indicates firm-level climate change and is calculated in Sautner et al. (2023). We control for year effects using two alternative specifications. Regression in Column (2) include year dummy variables. Year Dummy coefficients are unreported for brevity. We also include a time trend variable in Column (3) since the frequency of accounting fraud has been decreasing, particularly since the Sarbanes-Oxley Act (SOX). Z-statistics are reported in parentheses. All standard errors are adjusted for clustering by firm. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. Standard errors are reported in parentheses below the coefficients. Variables are as defined in Appendix 1.

	(1) Misstatement	(2) Misstatement	(3) Misstatement
Climate change exposure	0.052***	0.052***	0.053***
	(0.020)	(0.019)	(0.019)
Size		-0.031*	-0.030
		(0.019)	(0.018)
Market to Book		-0.001	-0.001
		(0.010)	(0.009)
Leverage		0.066	0.066
		(0.068)	(0.064)
ROA		0.110	0.108
		(0.092)	(0.091)
Intangibles		0.167	0.176
		(0.277)	(0.273)
Capital		-0.507**	-0.514**
		(0.237)	(0.236)
Sales Growth		0.015	0.015
		(0.016)	(0.016)
Inventory		0.263	0.249
		(0.347)	(0.345)
Negative book equity indicator		-0.144	-0.130
		(0.183)	(0.182)
Receivable		0.119	0.131
		(0.301)	(0.298)
Financing		0.044	0.041
		(0.088)	(0.087)
Interest cover		-0.032	-0.039
		(0.050)	(0.050)
Acquisition		0.097	0.091
		(0.163)	(0.160)
Time Trend			-0.056***
			(0.008)
Constant	-1.146**	-0.846	-0.690
	(0.516)	(0.519)	(0.507)
	0.052***	0.052***	0.053***
Observations	16,303	16,303	16,303
Pseudo R-squared	0.0773	0.0899	0.0807
Year FE	YES	YES	No
Industry FE	YES	YES	YES
SE Clustered by	Firm	Firm	Firm

Table4： Robustness tests: Alternative research designs.

Resstatement is a dummy variable which equals one if financial results for that year were intentional misstated and zero otherwise. Column (1) employs probit regression and inferences are based on standard errors clustered by firm and year, Column (2) employs probit model with random effect to control company specific effects and controls for year effect, following Lennox and Pittman (2010). Column (3) employs logit regression, controlling year effect and industry effects at the one-digit SIC level, following Erickson, Hanlon and Maydew (2005). Column (4) employs linear probability model (LPM) with year and industry fixed effects, following Christensen, D.M., et al. (2018). Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. All standard errors are reported in parentheses below the coefficients. Variables are as defined in Appendix 1.

	(1) Misstatement	(2) Misstatement	(4) Misstatement	(5) Misstatement
Climate change exposure	0.039**	0.071*	0.128***	0.002*
	(0.020)	(0.042)	(0.044)	(0.001)
Size	-0.055***	-0.039	-0.077*	-0.000
	(0.019)	(0.040)	(0.046)	(0.001)
Market to Book	-0.005	0.008	-0.000	0.000
	(0.006)	(0.015)	(0.027)	(0.000)
Leverage	0.050	0.068	0.178	0.000
	(0.057)	(0.144)	(0.172)	(0.002)
ROA	0.138	0.103	0.276	0.001
	(0.094)	(0.153)	(0.257)	(0.002)
Intangibles	0.135	0.252	0.343	-0.003
	(0.265)	(0.495)	(0.716)	(0.011)
Capital	-0.381**	-0.820*	-1.325**	0.011
	(0.156)	(0.425)	(0.636)	(0.007)
Sales Growth	0.019	0.042	0.028	0.000
	(0.016)	(0.025)	(0.037)	(0.001)
Inventory	0.687**	0.257	0.791	-0.015
	(0.305)	(0.683)	(0.842)	(0.016)
Negative book equity indicator	-0.138	-0.319	-0.416	-0.000
	(0.153)	(0.346)	(0.477)	(0.005)
Receivable	0.094	-0.323	0.482	0.031
	(0.229)	(0.456)	(0.812)	(0.021)
Financing	0.036	0.005	0.126	0.000
	(0.092)	(0.148)	(0.216)	(0.003)
Interest cover	-0.045	-0.043	-0.085	-0.002
	(0.042)	(0.079)	(0.126)	(0.002)
Acquisition	0.125	0.313	0.235	0.002
	(0.173)	(0.261)	(0.409)	(0.006)
Constant	-1.934***	-3.737***	-1.137	0.006
	(0.174)	(0.409)	(1.003)	(0.008)
Observations	16,303	16,303	16,303	16,303
Pseudo R-squared	0.0340		0.0911	
R-squared				0.101
Year FE	NO	YES	YES	YES
Industry FE	NO	NO	YES	YES
SE Clustered by	Firm, Year	Firm	Firm	Firm

Table 5: Robustness tests: Alternative misreporting measurements

This table presents results from estimating discretionary accruals (*Discretion*) as a function of climate change exposure and control variables. The models considered (1) Kothari (2006), (2) McNichols (2002) and (3) Dechow and Dichev (2002). This table presents results from a pooled ordinary least squares (OLS) regression with fixed year effect and fixed industry effect. Standard errors appear in parentheses and all standard errors are clustered by firm. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail), respectively. Sample includes 11,106 firm-years. Sample descriptive characteristics are found in Table 2. Variables are as defined in Appendix 1.

	(1) Discretion_Kothari	(2) Discretion_McNichols	(3) Discretion_Dechow and Dichev
Climate change exposure	0.253***	0.358**	0.358**
	(0.092)	(0.166)	(0.180)
Size	-1.572***	-3.108***	-2.732***
	(0.123)	(0.260)	(0.277)
Market to Book	0.627***	1.180***	1.316***
	(0.094)	(0.187)	(0.208)
Leverage	4.061***	9.342***	10.630***
	(0.974)	(2.230)	(2.510)
ROA	-0.486	-1.890**	-2.145**
	(0.426)	(0.869)	(0.958)
Intangibles	19.632***	27.092***	24.913***
	(2.706)	(5.348)	(5.782)
Capital	-4.457***	-8.458***	-7.910***
	(1.225)	(2.354)	(2.436)
Cashflow Volatility	0.640	1.005	0.963
	(0.715)	(1.404)	(1.514)
Sales Volitility	1.930	3.951	2.605
	(1.433)	(2.874)	(3.198)
Cash Holding	-2.463*	-6.451**	-5.639*
	(1.354)	(2.799)	(3.084)
Debt Issue	0.409*	1.053**	0.680
	(0.219)	(0.432)	(0.465)
Equity Issue	0.764	-0.567	-0.952
	(0.699)	(1.208)	(1.326)
Dividend	18.640***	12.699	19.608
	(5.797)	(11.759)	(12.527)
M&A Indicator	-1.432***	-1.429*	-0.977
	(0.401)	(0.771)	(0.801)
Constant	21.193***	35.492***	35.021***
	(1.841)	(3.353)	(3.477)
Observations	11,106	11,106	11,106
R-squared	0.427	0.452	0.441
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
SE Clustered by	Firm	Firm	Firm

Table 6: Robustness tests: Matched samples

This table presents results from utilizing three matching designs. In Panel A, misreporting firms are matched with non-misreporting firms based on the same industry, year, and total assets. Tabulated statistics test for a difference in firm-level climate change exposure between the two samples. Using an outcome matching sample, Column (1) reruns the baseline regression. Column (2) reruns a probit regression in Armstrong et al. (2012). Column (3) reruns a linear probability model (LPM), following Christensen et al. (2017). In Panel B, based on the outcome-based matching sample in Panel A, convergence is achieved between the treated group and control group in three dimensions (e.g., mean, variance and skewness) following entropy balance, as in Hainmueller (2012). The diagnostic test of entropy balance is presented in the Appendix. Panel C presents propensity score matching regression using *Misstatement* as dependent variable in Column(1)-(4) and *Discretion_Kothari* as dependent variable in Column (5)-(8). The treated group is matched with the control group by estimating a propensity score as a function of control variables and minimizing the differences in propensity scores while maximizing the differences in firm-level climate change exposure. Column (1) and Column (5) define the 50^{th} percentiles with respect to the total sample. Column (2) and Column (6) define the 50^{th} percentiles with within each industry group. Column (3) and Column (7) define the 40^{th} and 60^{th} percentiles with respect to the total sample. Column (4) and Column (8) define the 40^{th} and 60^{th} percentiles within each industry group. All variables are as defined in Appendix A. Standard errors are clustered at the firm level and reported in parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A: Industry, year and size matched sample

	Misreporting firm	Size, year& industry matched sample	Difference in Mean	
	N=193	N=193		
Variables	Mean1	Mean2	Diff	p-value
climate change exposure	1.607	0.621	0.987***	0.000

	(1)	(2)	(3)
	Misstatement	Misstatement	Misstatement
Climate change exposure	0.141***	0.116***	0.038***
	(0.042)	(0.035)	(0.009)
Size	0.004	-0.009	0.001
	(0.049)	(0.040)	(0.020)
Market to Book	0.017	0.020	0.006
	(0.034)	(0.031)	(0.013)
Leverage	0.777**	0.647*	0.280**
	(0.322)	(0.376)	(0.119)
ROA	-0.015	0.018	-0.005
	(0.237)	(0.231)	(0.091)
Intangibles	-0.201	0.076	-0.095
	(0.597)	(0.454)	(0.243)
Capital	-0.156	0.054	-0.060
	(0.501)	(0.341)	(0.204)
Sales Growth	0.010	0.033	0.005
	(0.052)	(0.054)	(0.021)
Inventory	-0.295	0.008	-0.118
	(0.635)	(0.436)	(0.254)
Negative book equity indicator	-0.717*	-0.680	-0.258*
	(0.390)	(0.415)	(0.141)
Receivable	0.027	-0.017	-0.005
	(0.504)	(0.465)	(0.194)
Financing	0.332	0.315	0.118
	(0.313)	(0.393)	(0.121)
Interest cover	-0.263**	-0.238*	-0.094
	(0.104)	(0.144)	(0.068)
Acquisition	-0.186	-0.110	-0.062
	(0.385)	(0.430)	(0.155)
Constant	0.133	-0.039	0.567**

	(0.620)	(0.413)	(0.246)
Observations	386	386	386
R-squared			0.086
Pseudo R-squared	0.0704	0.0594	
Year FE	YES	NO	YES
Industry FE	YES	NO	YES
SE Clustered by	Firm	Firm and Year	Firm

Panel B: Entropy Balance

	(1)	(2)
VARIABLES	Misstatement	Discretion_Kothari
Treat	0.302*	0.959***
	(0.175)	(0.349)
Constant	-0.458	19.942***
	(0.710)	(1.708)
Observations	308	8,885
R-squared		0.441
Year FE	YES	YES
Industry FE	YES	YES
SE Clustered by	Firm	Firm

Present for table

Panel C: Propensity Score Matching

	(1) Misstatement	(2) Misstatement	(3) Misstatement	(4) Misstatement	(5) Discretion_Kothari	(6) Discretion_Kothari	(7) Discretion_Kothari	(8) Discretion_Kothari
Climate Change Exposure	0.054***	0.052***	0.051***	0.050**	0.179**	0.180**	0.207**	0.214***
	(0.019)	(0.019)	(0.019)	(0.020)	(0.077)	(0.079)	(0.087)	(0.079)
Observations	15,834	15,584	12,612	12,364	10,544	10,586	8,436	8,308
Pseudo R-squared	0.0918	0.0886	0.0911	0.0909				
R-squared					0.415	0.421	0.440	0.435
Constant	-0.797	-0.879*	-0.813	-0.765	20.892***	20.725***	20.320***	20.122***
	(0.522)	(0.521)	(0.513)	(0.520)	(1.863)	(1.813)	(1.893)	(1.924)
Firm controls	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
SE Clustered by	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Table7: Difference-in-differences in misreporting behavior around the year 2015.

This table presents difference-in-differences estimates for the misreporting before and after 2015, using continuous variable (*Discretion_Kothari)* as the dependent variable. All regressions report estimates using as independent variables the interaction between *Post2015* and a dummy variable equal to 1 if the climate exposure indicator is above the 60^{th} percentile and 0 if the climate exposure indicator is below the 40^{th} percentile. Columns (1) and (2) use the total sample, comprising all firms with available climate exposure and financial data in COMPUSTAT. Column (1) define 40^{th} and 60^{th} percentiles in total sample. Column (2) define the 40^{th} and 60^{th} percentiles with each two-digit SIC industry group. All regressions include a constant, year fixed effects and industry fixed effect, and control for Size, Market to Book, Leverage, ROA, Intangibles, Capital, Cash Flow Volatility, Sales Volatility, Cash Holding, Debt Issue, Equity Issue, Dividend, M&A. Appendix A presents variable definitions. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

VARIABLES	(1) Discretion_Kothari	(2) Discretion_Kothari
HighClimatePost2015	2.038**	1.792**
	(0.860)	(0.876)
Constant	21.077***	20.011***
	(1.836)	(1.880)
Observations	8,879	8,887
R-squared	0.434	0.435
Firm Controls	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
SE clustered by	Firm	Firm

Table8: Mechanism Analysis

This table examines the impact of climate change on company financial misreporting behavior through the mechanisms of reduced accounting comparability and increased business uncertainty. Panel A presents the results from estimating a fixed effect model of accounting comparability (*Comparability*) as a function of climate change exposure and control variables. *Comparability* is measured following De Franco et al. (2011)'s output-based measure, which is based on the similarity of parameters from firm-specific linear regressions of GAAP earnings on returns for a firm and its industry peers. The detailed methodology for the calculation of *comparability* is presented in the Appendix. Column (1) includes all sample with non-missing variable. Column (2) and Column (3) excludes observations with zero *Climate change exposure* and rerun regression using only those firms with non-zero *climate change exposure*. Panel B presents the effects of climate change exposure on operating uncertainty, proxied by cash flow levels and revenue as a percentage of asset, and insolvency risk. Consistent with baseline regression, we include all control Variable used in estimating baseline regression. *Climate change exposure* indicates firm-level climate change and is calculated in Sautner et al. (2023). Appendix A presents variable definitions. All standard errors are clustered at the firm-level. *Standard errors* are reported in parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A: Climate change exposure and accounting comparability

VARIABLES	(1) Comparability	(2) Comparability	(3) Comparability
Climate change exposure	-0.024**	-0.023**	-0.030***
	(0.011)	(0.011)	(0.011)
Size	0.024	0.015	0.030
	(0.026)	(0.010)	(0.028)
Market to Book	-0.014*	-0.017**	-0.016**
	(0.008)	(0.007)	(0.008)
Leverage	0.101	0.098	0.120
	(0.077)	(0.075)	(0.089)
ROA	0.031	-0.075*	-0.025
	(0.052)	(0.044)	(0.050)
Intangibles	0.027	0.063	0.069
	(0.161)	(0.127)	(0.175)
Capital	0.059	0.014	0.142
	(0.109)	(0.082)	(0.110)
Sales Growth	0.002	0.013	0.009
	(0.013)	(0.011)	(0.012)
Inventory	-0.016	-0.136	-0.181
	(0.259)	(0.195)	(0.252)
Negative book equity indicator	0.042	0.038	0.046
	(0.051)	(0.054)	(0.062)
Receivable	0.116	0.146	0.187
	(0.203)	(0.159)	(0.189)
Financing	-0.027	-0.022	-0.022
	(0.035)	(0.035)	(0.036)
Interest cover	-0.016	-0.029*	-0.031*
	(0.016)	(0.017)	(0.018)
Acquisition	-0.037	-0.068	-0.090**
	(0.045)	(0.044)	(0.044)
Constant	-0.551***	-0.264**	-0.616***
	(0.159)	(0.108)	(0.179)
Observations	2,062	1,636	1,636
R-squared	0.155	0.164	0.169
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Firm FE	YES	NO	YES
SE Clustered by	Firm	Firm	Firm

Panel B: Climate change exposure and Operating Uncertainty			
	(1)	(2)	(3)
VARIABLES	Cash flow	Revenue	Insolvency risk
Climate change exposure	-0.263***	-0.987**	0.087***
	(0.099)	(0.486)	(0.027)
Size	0.312***	-4.319***	-0.065***
	(0.059)	(0.691)	(0.019)
Market to Book	0.702***	1.035*	-0.444***
	(0.113)	(0.600)	(0.026)
Leverage	-3.177***	1.909	3.743***
	(0.707)	(4.303)	(0.228)
ROA	62.916***	8.772**	-2.319***
	(1.131)	(4.219)	(0.192)
Intangibles	-7.731***	-30.338**	2.454***
	(2.017)	(12.793)	(0.374)
Capital	6.047***	-2.140	0.724***
	(0.622)	(6.643)	(0.163)
Sales Growth	-0.907**	9.161***	0.022
	(0.409)	(1.355)	(0.055)
Inventory	-6.789***	177.279***	-2.150***
	(1.382)	(17.443)	(0.435)
Negative book equity indicator	0.696	24.604***	1.232***
	(0.594)	(6.637)	(0.209)
Receivable	-5.040***	74.624***	-0.003
	(0.755)	(10.074)	(0.362)
Financing	-8.991***	6.268	-0.968***
	(0.794)	(4.830)	(0.143)
Interest cover	-0.538***	-15.228***	0.492***
	(0.155)	(1.234)	(0.034)
Acquisition	3.901***	45.132***	0.460***
	(0.524)	(5.750)	(0.108)
Constant	-1.245	120.785***	-0.249
	(1.646)	(30.040)	(0.484)
Observations	16,240	16,391	10,866
R-squared	0.765	0.403	
Pseudo R-squared			0.557
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
SE Clustered by	Firm	Firm	Firm

Table9: Cross-section Tests

This table presents results from our cross-sectional analyses. Panel A compares results for firms with high and low tangibility based on two measures of tangibility. Columns (1) and (2) divide groups based on *Tangibility_Berger*, as proposed by (Berger et al., 1996). Columns (3) and (4) are based on the proportion of intangible assets in total assets. Panel B compares results for large and small firms. Panel C conducts regression analyses on subsamples based on high versus low environmental litigation risk subgroups. We follow the methodology of Fard et al., (2020) in defining high environmental litigation risk industry groups, using 2-digit SIC codes: 49, 28, 29, 37, 13, 36, 35, 33, 38, 26, and 10. Panel D provides regression analyses on different groups based on financing from equity issues. Panel E divides groups based on high and low market leverage. Panel F presents a subsample regression analysis that focuses on concerns about global change, utilizing data from the Yale Climate Opinion Survey. The control variables employed in the regression analysis are consistent with those used in our baseline model. All regressions are controlled for year and industry fixed effects and standard errors are clustered at the firm level. *Standard errors* are reported in parentheses. Definitions of all variables are provided in Appendix 1. All continuous control variables are winsorized at the 1% and 99% levels. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A: High V.S. Low Tangibility

	Misstatement			
	(1)	(2)	(5)	(6)
VARIABLES	High Tangibility_Berger	low Tangibility_Berger	High Tangibility	Low Tangibility
Climate Change Exposure	0.085***	0.024	0.076***	0.015
	(0.025)	(0.026)	(0.020)	(0.029)
Constant	-2.361***	-2.232***	-1.761***	-1.884***
	(0.584)	(0.412)	(0.404)	(0.464)
Observations	8,152	8,151	8,151	8,152
Pseudo R-squared	0.187	0.0712	0.182	0.0913
Control	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
SE Clustered by	Firm	Firm	Firm	Firm

Panel B: Large V.S. Small Firms

	Misstatement	
Variables	(1)	(2)
	Large Corporations	Small Corporations
Climate Change Exposure	-0.000	0.066***
	(0.028)	(0.020)
Constant	-1.452*	-1.695***
	(0.855)	(0.490)
Observations	8,151	8,152
Pseudo R-squared	0.172	0.0927
Control	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
SE Clustered by	Firm	Firm

Panel C: High V.S. Low environmental risk firms

	Misstatement	
Variables	(1)	(2)
	High environmental litigation risk	Low environmental litigation risk
Climate Change Exposure	-0.078	0.082***
	(0.054)	(0.020)

Constant	-2.487***	-0.807
	(0.363)	(0.536)
Observations	6,627	9,676
Pseudo R-squared	0.106	0.151
Control	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
SE Clustered by	Firm	Firm

Panel D: High V.S. Low Equity Issue

	Misstatement	
	(1)	(2)
VARIABLES	High Equity Issue	Low Equity Issue
Climate Change Exposure	0.033	0.074***
	(0.021)	(0.015)
Constant	-1.907***	-1.956***
	(0.366)	(0.319)
Observations	8,152	8,151
Control	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
SE Clustered by	Firm	Firm
Pseudo R-squared	0.0868	0.144

Panel E: High V.S. Low Market Leverage

	Misstatement	
	(1)	(2)
VARIABLES	High Market Leverage	Low Market Leverage
Climate Change Exposure	0.076***	0.022
	(0.021)	(0.024)
Constant	-2.170***	-1.580***
	(0.443)	(0.388)
Observations	8,169	8,134
Pseudo R-squared	0.173	0.0924
Control	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
SE Clustered by	Firm	Firm

Panel F: High V.S. Low Worriedness about Global Warming

	(1)	(3)
VARIABLES	High	Low
Climate Change Exposure	0.041	0.066***
	(0.026)	(0.025)
Constant	-1.913***	-1.723***
	(0.410)	(0.417)
Observations	6,418	8,223

Pseudo R-squared	0.084	0.155
Control	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
SE Clustered by	Firm	Firm