

TCFD-aligned climate change disclosures and analyst forecasts

Dong Ding

Hefei University of Technology

dding@hfut.edu.cn

Bin Liu

University of Wollongong

liub@uow.edu.au

Jing Yu

University of Sydney

Jing.yu@sydney.edu.au

Millicent Chang

University of Wollongong

mchang@uow.edu.au

TCFD-aligned climate change disclosures and analyst forecasts

Preprint not peer reviewed

1. Introduction

Climate change has significantly affected the built economic environment in recent years, both physically and financially. For example, extreme weather conditions are detrimental to agricultural production and labour productivity at the macro level (Fisher et al., 2012; Graff Zivin and Neidell, 2014), as well as profitability in some specific industries at the firm level (Hong et al., 2019; Hugon and Law, 2019). Additionally, climate change policies lead to shifts in market share towards firms with low adjustment costs (Kennard, 2020) and investors react positively to green bond issuances as issuers are able to signal their climate commitments by selling green bonds (Flammer, 2021). These adverse impacts have raised investor awareness of climate change issues, and hence institutional investors recognise and evaluate them when selecting portfolio firms (Krueger et al., 2020). However, investors may have difficulties in understanding firms' climate risk exposure due to a lack of disclosure by firms (Ilhan et al., 2023). Thus, disclosure initiatives such as the CDP Reporting (formerly Carbon Disclosure Project), the Global Principles Reporting, and the TCFD recommendations assist firms in making effective climate change disclosures to provide decision-useful information for investors. These reflect an increasing demand for firms to disclose transparent climate change information for better investment decisions, which is critical to information users, particularly for stock market participants to assess exposure to climate risks.

Financial analysts are an important group among stock market participants and serve as information intermediaries between firms and investors by gathering and interpreting information to generate earnings forecasts and investment recommendations. Climate change information is important to analysts due to climate-related effects on firm financial performance. It is well documented that climate risks affect cost of capital (Balvers et al., 2017), firm earnings (Hong et al., 2019; Hugon and Law, 2019), asset values (Baldauf et al., 2020; Giglio et al., 2021b), and stock returns (Bolton and Kacperczyk, 2023). On the other hand, firms are under pressure to disclose more climate change information due to regulatory changes, to signal their climate commitments, and to help outsiders assess their climate risk exposures (Hahn et al., 2015). These climate change disclosures may also contain meaningful information on firm resilience to climate risks and so provide a holistic view of their potential financial implications to analysts. Although these studies provide indirect suggestions on the increasing importance of climate change information to financial analysts, what we know so far makes it difficult to understand its value to them.

Research has shown that non-financial disclosures convey useful information to analysts, especially CSR disclosures. [Dhaliwal et al. \(2012\)](#) employ the issuance of stand-alone CSR reports to proxy for CSR disclosure and find that CSR reporting is positively associated with earnings forecast accuracy. [Muslu et al. \(2019\)](#) similarly measure CSR narratives by aggregating tone, readability, and document length into a disclosure score index and document that firms with higher CSR disclosure scores have more accurate analyst forecasts. In addition to CSR disclosures, [Becchetti et al. \(2013\)](#) and [Cui et al. \(2018\)](#) use CSR strengths and concerns to measure CSR engagement and show that a higher level of CSR engagement is negatively associated with analyst forecast dispersion and error. Martínez-Ferrero, Ruiz-Cano and García-Sánchez (2016) measure CSR disclosures using international indicators of GRI guidelines and report that CSR disclosures significantly enhance analyst forecast accuracy. More recently, Ben-Amar, Herrera, and Martinez (2024) find that climate risk disclosures increase forecast precision and reduce dispersion only when investors perceive climate risks to be financially material at the industry level.

The current study builds on prior work by investigating the effect of firm level climate related financial disclosures on analyst forecast accuracy and dispersion. Through the application of textual analysis, a firm's climate change narrative is converted into a disclosure score. This study differs from the most recent study, Ben Amar et al (2024) as climate change disclosures are evaluated according to their alignment with the TCFD reporting framework. These recommendations have become a foundation for standards in climate related disclosures globally, influencing developments in regulation and defining reporting requirements. The TCFD framework is arguably the predominant climate reporting framework, given its impact on the European Union's Sustainable Finance Disclosure (SFDR), and incorporation into the International Financial Reporting Standards (IFRS). IFRS S1 and S2 standards integrate TCFD recommendations comprehensively and IFRS has taken over the monitoring of progress on climate-related disclosures. Since their introduction in 2017, there has been widespread adoption worldwide with TCFD supporters in 89 countries and jurisdictions, covering nearly all sectors of the economy with a total market capitalisation more than \$25 trillion. Countries including Brazil, Hong Kong, Japan, New Zealand, Singapore, Switzerland, the UK, and the EU have also introduced mandatory TCFD reporting for certain entities. Another difference is our use of the Term Frequency-Inverse Document Frequency (TF-IDF) method in natural language processing (NLP), as used in Engle et al (2020) to transform text into numerical vectors. This method is superior to the Bag-of Words (BoW) method as it adjusts for word

importance by considering both the frequency and rarity of a term within a document across the corpus. We customise the method to the TCFD framework to obtain our own measure of climate risk from disclosures, making it distinct the Ceres score in [Ben-Amar et al. \(2024\)](#). Our sample is also more extensive, covering countries beyond the US, who are strong supporters of TCFD framework and publish their annual reports in English.

Textual analysis via NLP is chosen in this study because it allows us to convert climate change narratives into numerical data in a systematic way. Four category-level climate change vocabularies are created based on TCFD category-aligned disclosures from TCFD supporting firms,¹ and combined into an aggregate vocabulary. TCFD-aligned disclosures are ideal due to the wide support for TCFD recommendations in over 100 jurisdictions (TCFD, 2022) and the ISSB's adoption of the TCFD framework for international standards. With the aggregate and category-level climate change vocabularies, textual analysis of annual reports is performed to compute aggregate and category-level climate change similarity scores as a measure of climate change disclosures. Our firm-level climate disclosure measures essentially capture the alignment of a firm's climate narratives with the TCFD's recommended reporting guidelines. This measure offers several important advantages for empirical analysis. First, the TCFD framework focuses on financially material information on climate risk needed by among others, investors, lenders, and insurance underwriters. Ilhan et al. (2023) find that nearly 60% of investors engage with firms to disclose climate change information in line with TCFD recommendations. Second, following the TCFD recommendations, our climate disclosure measure quantifies a firm's climate-related Governance, Strategy, Risk Management and Metrics & Targets, providing a holistic view of climate change disclosures through not only risks but also opportunities. Third, the TCFD framework is the most consistent and comparable climate risk reporting framework, allowing comparison across firms from different countries. Finally, the TCFD recommends the climate-related disclosure to be included in annual reports (TCFD, 2017), allowing us to examine its relevance to financial indicators in the annual reports.

¹ These four categories are as follows: 1) Governance (disclose the organisation's governance around climate-related risks and opportunities); 2) Strategy (disclose actual and potential impacts of climate-related risks and opportunities on the organisation's businesses, strategy, and financial planning where such information is material); 3) Risk Management (disclose how the organisation identifies, assesses, and manages climate-related risks); and 4) Metrics and Targets (disclose the metrics and targets used to assess and manage relevant climate-related risks and opportunities where such information is material).

We conceptualise our disclosure measure as a proxy for a firm's material climate change disclosure and hypothesize that extensive climate change disclosure in a firm's annual report is associated with a robust improvement in analyst forecast accuracy. If investors are placing increasing importance on climate risk, analysts' forecasts should reflect their assessment on the value-relevance of climate change information on the firm's future performance to help information users (i.e., investors) incorporate such information into their decision making. Second, unlike some investors, financial analysts have expertise in processing and analysing complex information and estimating their effect on financial performance. As such, climate information is new and can be complex in nature and reported qualitatively without clear connections to measures of financial performance such as revenues, expenses, profits, assets, or liabilities. As [Krueger et al. \(2020\)](#) noted, investors are "still learning how to deal with these risks" (page 1087). [TCFD \(2017\)](#) also stated that complex climate risks profoundly impact firms at all levels, from upstream operations to downstream markets, through multiple channels including operations and assets, supply chains, and shifts in customer preferences for goods and services. Simply relying on climate disclosure on risks and opportunities is far from enough. An understanding of a firm's overall path to climate change mitigation and adaptation requires in-depth knowledge and dedicated analytical skills. As important information intermediaries, financial analysts can use their competitive advantage to translate a firm's numerical climate disclosure and qualitative discussions about climate governance and strategies into financial valuation, hence operationalizing the connection between climate disclosures and financial reporting.

We conduct empirical tests on a multi-country sample which includes firms from Australia, Canada, France, the United Kingdom (UK) and the United States (US) over the period from 2010 to 2019. To start, we perform numerous validation tests on our novel firm climate change disclosure measure. First, we identify plausible patterns in our climate change disclosure measure across industries and countries. The disclosure score is relatively higher in the Utilities, Materials and Energy sectors, which are most vulnerable to climate change risks. At the country level, firms in France and the UK provide the most comprehensive climate change disclosures, whereas the US firms exhibit the lowest levels of disclosure. This variation aligns with the climate regulations in these countries. Further, to sharpen identification, we employ two exogenous shocks to firm-level climate change disclosures to check whether our climate disclosure measure increases following regulatory reforms that mandate climate disclosures. In a difference-in-difference (DiD) setting, we find that firms with high equity

ownership by French institutional investors show increased climate change disclosure scores in annual reports following Article 173 which mandated climate disclosure for both listed firms and institutional investors in France. We further show that climate disclosure scores for firms in France and the UK significantly increased after the passage of EU Non-Financial Reporting Directive in 2013, compared to those in Australia, Canada, and the US. Collectively, the evidence substantiates the validity of our firm-level climate change disclosure measure.

Next, we test the relationship between firm-level climate change disclosure and analyst earnings forecast quality. In support of our hypotheses, we find that the climate change disclosure measure is negatively associated with forecast error and dispersion. This relationship holds across all four categories of climate change disclosure, namely, Governance, Strategy, Risk Management, and Metrics and Targets. Country level analysis shows variation in analysts' use of aggregate and categorial disclosure on climate change. For example, in Australia and the UK, the aggregate and Governance, Strategy and Risk Management scores affect forecast error, but in Canada and France, the aggregate and category scores do not affect forecast error. Additional analysis reveals that the relation between firm-level climate change exposure and analyst forecast quality measures is more pronounced among TCFD supporting firms.

We then delve deeper to explore how firm-disclosed climate change exposure contributes to information available to analysts to improve their earnings forecast accuracy. Utilizing the future earnings response coefficient as an indicator of the degree to which future earnings are reflected in stock prices, we find that the incorporation of information about future earnings in stock prices increases with climate change disclosure. This finding confirms the informativeness of firm-level climate disclosures and aligns with the informational role of analysts in assisting investors to interpret the financial implications of climate change disclosures.

This study contributes to the emerging literature on corporate non-financial information disclosure. Parallel to studies that investigate the economic effects of non-financial information disclosure (Dhaliwal et al., 2012; Fiechter et al., 2022; Gibbons, 2024), a growing literature makes an attempt to measure market- or firm-level climate change risk through textual analysis on documents such as newspapers (Engle et al., 2020), corporate earnings conference calls (Sautner et al., 2023) and CSR reports (Dhaliwal et al., 2012; Muslu et al., 2019). These studies tend to rely on voluntary disclosures that may involve a cheap talk or redundant information irrelevant to a firm's valuation (Bingler et al., 2022; Matsumura et al., 2024). Another related strand of literature investigates how non-financial information disclosure affects the

forecasting accuracy of sell-side analysts. For example, analysing nonfinancial information content in mandated disclosures, [Dhaliwal et al. \(2012\)](#) find that the issuance of stand-alone CSR reports provide useful non-financial information and thereby improve analysts' earnings forecast accuracy in an international sample. [Ben-Amar et al. \(2024\)](#) document that 10-K climate risk disclosures manually collected from Ceres lead to greater forecast accuracy and lower dispersion in the US. Extending this literature, the novelty in our study lies in (1) the expanded emphasis on both climate risks and associated opportunities and (2) the identification of climate-related information that matters to market participants in annual reports ([Campbell et al., 2014](#); [Kravet and Muslu, 2013](#)). Compared with climate disclosures in stand-alone sustainability reports, firms and managers making private disclosure decisions on quantitative or qualitative information in the annual reports directly link climate change information to financial performance indicators, leading to improved information content of climate narratives in financial reports.

Additionally, given that many jurisdictions have regulations in place (such as Regulation S-K in the US) that require firms to disclose financially material information, any climate narratives extracted from annual reports are expected to be more financially relevant and less prone to managerial discretion. For example, the SEC shows that physical climate risk interrupts firms' operation, and logistics, and imposes other risks related to indirect consequences of regulation. Therefore, climate-related risks that materially affect financial performance should be disclosed to investors ([Kim et al., 2023](#)). This way, our study offers an important solution to discern the financial materiality of firm-level climate change disclosures. While prior studies recognize the importance of managing material climate strengths and weaknesses ([Flammer et al., 2019](#); [Gibbons, 2024](#); [Khan et al., 2016](#)), the literature has grappled with the measurement of such materiality. Early studies use third-party environmental, social and governance (ESG) ratings to capture material ESG issues, but ratings-based materiality measures may not be reliable and can be driven by firm fundamentals such as size, growth rate and profitability ([Ahn et al., 2024](#)). Our findings show that climate change disclosure, made in audited annual reports and aligned with TCFD reporting framework, reflects the financial materiality of a firm's climate change disclosures, and contributes towards investors' valuation assessment.

Finally, our work extends recent studies on the effects of climate risks on analyst earnings forecasts. The prior literature suggests that financial analysts' forecasting can be affected by climate change through a cash flow effect or a behavioural reason. For example, [Addoum et](#)

al. (2020) support a cash flow channel by showing that while analysts do not immediately react to observable temperature shocks, their earnings forecasts do account for these shocks by quarter-end in many US industries. In support of a behavioural explanation, Cuculiza et al. (2021) report that pessimistic earnings forecasts are issued during periods of increasing temperature. Han et al. (2020) find that analysts experiencing climatic disasters make less accurate earnings forecasts due to distracted attention caused by these disasters. Distinct from the existing literature, we attempt to explain the impact of firm-level climate change disclosures on analyst belief updating from the perspective of firm-disclosed information. We uncover an important economic channel that leads to the improved quality of their earnings forecasts. We show that current stock prices become more responsive to new financial performance information in firms with extensive climate disclosures, lending support to an information transmission channel through which analysts process disclosed climate information and embed it into their forecasts. These findings on the nonfinancial information disclosure are complementary to a large body of literature highlighting the role of sell-side analysts in improving the *financial* information environment of firms (Beyer et al., 2010; Bhushan, 1989; Lang and Lundholm, 1996). The significant impact of material climate disclosure on analysts and investors also adds a new perspective for policymakers and governments on mandating firms to disclose climate change information aligned with TCFD recommendations. Our findings endorse the growing number of governments advocating TCFD recommendations as a policy foundation for climate change disclosure regulations (TCFD (2022)).

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and develops hypotheses, and Section 3 describes the sample selection, variable construction, and research design. Section 4 reports empirical results, followed by economic mechanism tests in Section 5 and robustness tests in Section 6. Section 7 concludes.

2. Hypothesis Development

We explore the effect of climate change disclosure in annual reports on analyst forecasts. This investigation hinges on two key factors: the value relevance of climate disclosures and the extent to which analysts incorporate this information. The hypotheses are formulated around these two factors, drawing insights from the existing literature. Firms are required to disclose financially material risks. Yet, the decision to disclose a firm's climate change exposure depends on managers' private risk materiality assessment, made on a case-by-case basis. For example, devoid of carbon pricing regulations, high carbon emissions may affect a firm's long-term valuation but not undermine its near-term earnings. As such, managers may

not disclose its carbon emission mitigation plans when they are perceived as value irrelevant ([Christensen et al., 2021](#); [Matsumura et al., 2024](#)). Another example can be found in [Addoum et al. \(2023\)](#), whereby extremely cold temperatures in Spring hurt earnings of travel-related industries but generate good earnings for industries of leisure products. In such cases, firms may not disclose climate change exposure when they are beneficiaries of climate change. Essentially, without mandated, standardized climate change reporting frameworks, climate change information disclosed in annual reports can be viewed as voluntary. That being said, given that capital markets infer firm risks from corporate filings ([Campbell et al., 2014](#); [Kravet and Muslu, 2013](#)), climate-related narratives provided in annual reports are subject to investor scrutiny, and therefore can be portrayed as firm-disclosed financially material climate change exposure.

2.1 Aggregate climate change disclosure

The existing literature ([Lehavy et al., 2011](#); [Loughran and McDonald, 2014](#)) suggests that sell-side financial analysts use information from firms' annual reports to make investment recommendations. Taking the sell-side analyst's perspective, there are good reasons to believe that they will respond to and incorporate material climate change information disclosed by firms. First, the textual analysis of climate narratives in annual reports provides a complete picture about a firm's climate change disclosure. In alignment with the TCFD reporting framework, our measure takes into consideration the governance, strategic, risk management, and metrics and targets aspects of a firm's climate change disclosure. This information set constitutes soft information to investors, complementary to other hard, numerical information such as extreme weather conditions and the amount of carbon emissions. As the soft information is complex, due to their expertise, analysts have a competitive advantage over other users of this information when they incorporate the climate change information into their valuation models. In support, [Lehavy et al. \(2011\)](#) show that 10-K disclosure complexity attracts analyst following and analysts dedicate more effort to processing complex information. Building on growing evidence on the real effects of climate change on firm profits ([Addoum et al., 2023](#); [Pankratz et al., 2023](#)), the soft information contained in annual reports is expected to incur greater analyst efforts and assist them in making precise earnings revisions.

Moreover, a comprehensive climate change disclosure measure can also help analysts to form a complete view of the impact of a firm's climate change disclosure on near-term earnings. For instance, [Cohen et al. \(2020\)](#) report that carbon-intensive firms tend to be most innovative in green technologies. While high emissions indicate greater climate transition risks

for polluting firms, the potential market value of their green technologies counteracts or even reverses the adverse effects of carbon emissions. By scrutinizing climate change disclosure provided in annual reports, analysts are expected to gain a comprehensive picture of firms' overall climate change downside risks and upside opportunities, and make more accurate earnings forecast revisions based on these material climate change disclosures.

Taken together, the above discussions support the notion that financially material climate change disclosure can help analysts to understand the impact of firm-level climate change exposure on near-term earnings. Using analyst forecast accuracy and dispersion as proxies for analyst forecast quality (Chen et al., 2015; Chen et al., 2017; El Ghoul et al., 2023; Michaely et al., 2024), the first hypothesis is stated as follows:

H1: Firm-level aggregate climate change disclosure improves sell-side analyst forecast accuracy and reduces forecast dispersion.

Since TCFD-aligned climate change disclosures in aggregate are predicted to provide useful information on the financial implications of climate change, it is expected that more specific disclosures on how firms take initiatives to govern, identify, and manage climate risks through informative content under the four TCFD categories of Governance, Strategy, Risk Management, and Metrics and Targets would allow analysts to garner a more complete understanding of risks and opportunities facing firms. We briefly discuss our expectations of how each of these TCFD categories affect analyst forecasts.

2.2 Governance climate change disclosure

Corporate governance is informative to assess information disclosure quality (Bhat et al., 2006). The survey results of information users' views on the usefulness of TCFD-aligned climate change disclosures published in the 2019 TCFD Status Report (TCFD, 2019) reveal that 75% of respondents noted an improvement in disclosure quality due to an increasing number of firms accounting for governance of climate risks at board and management levels. Given that information disclosure quality is a key factor for analyst forecasts (Hope, 2003; Lang and Lundholm, 1996), analysts can use corporate governance structures to assess disclosure quality. Bhat et al. (2006) attribute the importance of corporate governance to analysts to the integrity of financial disclosure and the role of governance disclosures in reducing information uncertainty surrounding future firm performance. Corporate governance also affects the quality of environmental information disclosures. For example, sustainability committees as a part of corporate governance are increasingly being established to engage

stakeholders by identifying which sustainable issues matter to them, as well as providing board oversight of management reporting of environmental information. Therefore, firms with sustainability committees have a responsibility for ensuring sustainability reporting quality and transparency (Michelon and Parbonetti, 2012; Velte and Stawinoga, 2020). If firms have better corporate governance structures (i.e., an environmental committee or sustainability leadership team) for climate change issues, analysts will understand the positive effect on information disclosure quality and rely more on climate change disclosures in their assessments, hence resulting in reductions in forecast error and dispersion. Overall, we expect better governance disclosures facilitate analysts' assessment of climate change disclosure quality and result in improved earnings forecasts.

H2a: Firm-level governance climate change disclosure improves sell-side analyst forecast accuracy and reduces forecast dispersion

2.3 Strategy climate change disclosure

From an analysis of TCFD recommendations, Eis et al. (2019) document that climate risks arising from physical and transition risks² have profound effects on both upstream firms themselves and downstream markets through multiple channels: direct physical impact on firms' operations and assets, impact on supply chains and subsequent production capacity, and impact on market changes such as shifts in customer preferences for goods and services. This reflects how analysts assess the financial impact of climate risks based on information disclosed under the Strategy category. The significant financial impact of physical and transition risks has also attracted analyst attention. Cuculiza et al. (2021) find that analysts issue more accurate earnings forecasts by downgrading their forecasts for firms affected by extreme temperatures, due to the adverse effect on firm profitability. Ramelli et al. (2021) report that analysts incorporate the effect of the first Global Climate Strike on future operating performance of carbon intensive firms into earnings forecasts, leading to downward revisions of their forecasts. Together, these studies indicate that analysts assess the financial implications of climate risks, and thus climate change disclosures under Strategy can aid analysts'

² The TCFD (2017) shows that physical climate risks can be event-driven (acute risks) such as extreme weather events, or longer-term shifts (chronic risks) in climate patterns that may result in sea-level rise and heat waves. Climate transition risks refer to risks associated with the transition to a lower-carbon economy including policy risks, technology risks, and reputation risks.

information integration through a better understanding of the potential impact on firm operations, leading to improved forecasts.

H2b: Firm-level climate change disclosure on strategy improves sell-side analyst forecast accuracy and reduces forecast dispersion

2.4 Risk management climate change disclosure

Weinhofer and Busch (2013) document that an effective approach to managing climate risks is to integrate them into the corporate risk management process regarding how firms identify, assess, and implement activities to manage risks, which is consistent with TCFD recommendations under the Risk Management category. Strong risk management on environmental issues gain benefits in capital markets. For example, Sharfman and Fernando (2008) use environmental performance as a proxy for environmental risk management and find that cost of capital is negatively associated with environmental risk management, suggesting that better environmental risk management can reduce a firm's financing costs. Sustainability risk materiality³ assessment is also an important part of the corporate risk management process. Khan et al. (2016) demonstrate that firms with higher ratings on the materiality of sustainability issues reflect better risk management and have better future performance. Matsumura et al. (2024) show that when climate risks are expected to be material, firms disclosing climate change information experience a reduction in the cost of capital. Therefore, information disclosed under Risk Management is relevant to analysts who require credible information to assess climate risks. This is because sustainability activities and risk materiality assessments within corporate risk management processes are expected to have significant financial implications for firms.

TCFD (2017) encourages firms to conduct risk materiality assessments when determining whether climate risks are integrated into overall risk management, which is consistent with other financial risk assessments. Krueger et al. (2020) argue that climate risks are being perceived as a financially material issue by firms and climate risk materiality has a positive

³ According to the Financial Accounting Standards Board (FASB) 2018 conceptual framework, materiality is defined as: "the omission or misstatement of an item in a financial report is material if, in light of surrounding circumstances, the magnitude of the item is such that it is probable that the judgment of a reasonable person relying upon the report would have been changed or influenced by the inclusion or correction of the item." This is consistent with the materiality definition used by the US Securities and Exchange Commission (SEC). The International Integrated Reporting Framework describes materiality as "a matter is material if it could substantively affect the organisation's ability to create value in the short, medium or long term." The document is available [here](#).

effect on climate risk management. In this regard, analysts interpret high levels of materiality as signals of better risk management, which potentially reduces information uncertainty for analysts. [Flores et al. \(2019\)](#) emphasise that risk materiality is particularly relevant to analysts since firms are required to disclose what really matters, which alleviates the information overload. They further find that analysts make more accurate earnings forecasts among firms reporting information based on the materiality principle as one important Integrated Reporting principle. Therefore, if firms disclose information that climate risks are integrated and identified as financially material in an overall risk management process, analysts will incorporate this information into their forecasting models, leading to more accurate earnings forecasts.

H2c: Firm-level climate change disclosure on risk assessment and management improves sell-side analyst forecast accuracy and reduces forecast dispersion

2.5 Metrics and Targets climate change disclosure

[TCFD \(2017\)](#) recommends that organisations disclose some key metrics tailored to measure climate risks and opportunities. The most commonly used carbon metric⁴ comprises various indicators on GHG emissions, such as carbon intensity and total carbon emissions, which involves calculations in line with GHG protocols by scope, including Scope 1 and Scope 2, and if appropriate, Scope 3.⁵ [Eccles et al. \(2011\)](#) also highlight that among environmental metrics, equity investors pay close attention to carbon emissions, reflecting their concerns about the negative impact on equity values.

A number of studies document that the stock market imposes penalties on firms with high carbon emissions as a negative association is found between firm value and carbon emissions ([Clarkson et al., 2015](#); [Griffin et al., 2017](#); [Matsumura et al., 2013](#)). On the other hand, firms benefit from disclosing carbon emission information. For example, [Bolton and Kacperczyk \(2021\)](#) show that firms with carbon emission disclosures have lower cost of capital because investors face less information uncertainty. In addition, [Matsumura et al. \(2013\)](#) find that

⁴ The [TCFD \(2017\)](#) introduced six broad categories of climate-related metrics, including GHG emissions, energy, water, land use, location, and risk adaptation and mitigation. Similarly, [Eccles et al. \(2011\)](#) provide a list of eight environmental metrics: total CO₂ emissions, CO₂ intensity, environmental policies (energy efficiency policy and emissions reduction initiatives), costs from violating environmental regulations (environmental fines and number of environmental fines), waste (total waste), and energy (energy consumption).

⁵ See: [Implementing the Recommendations of the Task Force on Climate-related Financial Disclosures](#) (TCFD, 2017, pp.43-44).

carbon emission disclosures mitigate the negative firm-value effects of carbon emissions and firms with emission disclosures have a higher market value than firms without disclosures. These studies suggest that carbon emission disclosures convey value-relevant information to capital markets, which implies that analysts could integrate useful information from disclosures into their valuation models. [Aerts et al. \(2008\)](#) employ a measure of environmental disclosure related to pollutant emissions, environmental fines, energy consumption, and waste management, and find that improved environmental disclosures are associated with greater forecast accuracy. [Dal Maso and Rees \(2016\)](#) find a significant reduction in analyst forecast errors among firms with carbon emission disclosures, because analysts can assess future costs and benefits regarding carbon emissions through disclosures, and issue accurate earnings forecasts. Thus, disclosures under the Metrics and Targets category, which contains information on carbon emissions and other metrics (i.e., energy consumption), are likely to be useful to analysts when assessing future firm performance.

H2d: Firm-level climate change disclosure on metrics and targets improves sell-side analyst forecast accuracy and reduces forecast dispersion

2.6 TCFD supporters

Institutional theory ([Oliver, 1991](#)) proposes that social norms and rules potentially influence firm disclosure behaviours and practices to converge over time ([Cormier et al., 2005](#)). These disclosure convergences also reflect firm commitments to high-quality reporting, especially in accounting reporting standards ([Hail et al., 2010](#); [Leuz and Wysocki, 2016](#)). Similarly, as a coordinated effort to address global climate change issues, the TCFD is viewed as an international convergence of climate change reporting to a high standard with more disclosures in each category ([TCFD, 2022](#)).

Previous studies find a positive effect of a firm's commitment to increased disclosure, where [Leuz and Verrecchia \(2000\)](#) view a shift to an international reporting scheme in financial statements as a commitment to high quality financial disclosure, and find that German firms adopting IFRS have lower information asymmetry. [Dhaliwal et al. \(2011\)](#) argue that CSR disclosures reflect firms' commitment to improving CSR performance, especially for firms facing social pressure in emerging markets, and voluntary disclosure commitment is positively associated with reduced cost of equity capital. These studies indicate firms' commitments to higher quality disclosure contain information that can be perceived by investors to be useful.

The TCFD (2022) shows that an increasing number of firms have become TCFD supporters since its launch in 2017. These supporting firms disclose more comprehensive climate change information aligned with TCFD recommendations and provide analysts with informative content, such that convergence in analyst earnings forecasts is expected among them. In this study, we identify TCFD supporter status as a signal of a firm's commitment to a higher level of climate change disclosures⁶ and predict that analysts can assess these commitments and issue more accurate earnings forecasts for supporting firms. However, Bingler et al. (2022) argue that firms with commitments to climate change disclosure appear to “cherry-pick” on non-material disclosures, and they call for the mandatory adoption of TCFD recommendations. Regardless, the third hypothesis is as follows:

H3: Compared to non-TCFD supporters, firm-level climate change disclosure in aggregate and by category improves sell-side analyst forecast accuracy and reduces forecast dispersion

3. Sample Selection and Research Design

3.1 Sample and Data

The empirical analysis focuses on five major TCFD supporting countries, including Australia, Canada, France, the UK, and the US because firms in these countries are among the first disclosers in support of the TCFD framework, and the financial reports are mostly in English. To illustrate the choice of sample countries, we show in Figure 1 that the countries with the highest number of firms supporting TCFD are Japan, the UK, and the US, followed by Australia, France, and Canada. However, due to the unavailability of financial reports in English among Japanese firms on LSEG's Workspace, our sample is limited to the remaining five countries. We begin our analysis from 2010 to retain a homogenous sample because most of the sample countries implemented a series of climate change reporting guidelines at the start of our sample period in 2010.⁷ To keep the computation manageable, as well as to ensure the

⁶ TCFD defines a supporter as “for companies, support is a commitment to work towards their own implementation of the TCFD recommendations.”

⁷ For example, under the Australian Securities Exchange Listing Rules in 2010, companies are required to disclose in their annual reports the extent to which they have followed the Corporate Governance Council's Recommendations and Principles on a “comply or explain” basis, one of which (i.e., Principle 7) stated that companies should consider all material business risks - “including environmental, sustainability, financial reporting and market-related risks”. In the same year, Canadian Securities Administrators published the Guidance on Environmental Reporting (i.e., CSA Staff Notice 51-333) to guide issuers on existing disclosure requirements

generalisability of our results, the initial firm-level sample is formed by selecting all listed firms ranked in top 300 in Australia, top 300 in Canada, top 150 in France, top 350 in the UK, and top 3000 in the US based on stock market capitalization in any given year from 2010 to 2019. This criterion ensured that the sample firms represent more than 90% of the local market capitalisation.

Firm annual reports are the primary source used to extract qualitative climate change information disclosure. [TCFD \(2017\)](#) recommends that firms make climate change disclosures in their mainstream annual filings, which is conducive to promoting shareholder engagement and a wider use of disclosed information. Based on the TCFD survey in 2022 ([TCFD, 2022](#)), 70% of 226 company respondents disclosed TCFD-aligned climate change information in annual reports or financial filings, an increase of 25% from 2017. While all publicly listed firms are required to file annual reports, quarterly earnings conference calls are voluntary and therefore unavailable for many firms. [Nagar and Schoenfeld \(2024\)](#) report that only approximately half of listed firms have earnings conference calls data in the LSEG database. In our sample, approximately 25% of firm-years with reported climate change information in annual reports were unavailable in the earnings conference calls sample in [Sautner et al. \(2023\)](#). Hence, extracting climate narratives from annual reports also alleviates sample selection bias.

To compute firm-level climate change disclosure in alignment with TCFD reporting framework, we gather the annual reports of US firms (i.e., 10-K filings) from the Securities and Exchange Commission Electronic Data Gathering, Analysis, and Retrieval (SEC EDGAR) system, Canadian firms from the System for Electronic Document Analysis and Retrieval (SEDAR), and annual reports of other firms from LSEG Workspace and corporate websites. We then merge the sample firm data with data from several other databases to form the final sample as follows: stock trading and accounting data taken from Compustat Global and CRSP databases, financial analyst earnings forecast data from I/B/E/S, and performance data from LSEG ESG database. We exclude financial firms with SIC codes between 6000 and 6999. Firms with negative book equity values are also omitted. The final sample includes 3,057

relating to environmental matters, including climate change. In France, *The Grenelle II Act* regulated listed firms to disclose carbon emissions data in addition to environmental and social information on annual reports. The UK updated their *Company 2006 Act* in 2013, which mandated listed firms to report carbon emissions information. In 2010, the Securities and Exchange Commission in the US issued the *Commission Guidance Regarding Disclosure Related to Climate Change*, which provided guidelines to assist listed firms in satisfying information disclosure requirements regarding climate change matters under the existing SEC disclosure rules.

unique firms with 16,926 non-missing firm-year observations. Table 1 illustrates the process of how the final sample and each of the country-specific samples were derived.

[Insert Table1 about here]

3.2 Analyst Earnings Forecast Measures

The I/B/E/S database is recognized as a source for sell-side analyst forecast data. However, prior studies highlight some important issues regarding the earnings estimates when using the summary and detail files, such as rounding errors in the I/B/E/S summary file (Payne and Thomas, 2003) and rewriting issues in the I/B/E/S detail file (Call et al., 2021). In addition, Law (2023) reveals that I/B/E/S announced its intention to anonymize 88 estimators and their analysts' names due to regulatory compliance, which significantly affects individual analyst estimates in the detail file. Since the summary file is less affected by these issues (Call et al. (2021)), our analysis employs the I/B/E/S summary file to compute analyst forecast error and dispersion measures.

Specifically, we measure the analyst earnings forecast accuracy annually using forecast error computed as the average value of absolute difference between monthly mean earnings forecasts and actual earnings, scaled by stock price at the beginning of the year (Chen et al., 2015; Hope, 2003; Lang and Lundholm, 1996). The specific calculation is carried out using the following equation:

$$FError(X)_{i,t} = \left(\frac{1}{N} \sum_{j=1}^N |FEST_{i,j,t} - ACT_{i,t}| \right) / P_{i,t} \quad (1)$$

where $FEST_{i,j,t}$ is analyst mean earnings forecast in month j for firm i in year t . $ACT_{i,t}$ is actual earnings value of firm i at year t . $P_{i,t}$ is stock price. Following Dhaliwal et al. (2012), we set X equal to 0, 1, or 2, representing earnings forecasts made in year t for current year 0, one year ahead (1) and two years ahead (2).

Analyst forecast dispersion is defined as the average value of monthly standard deviations of analyst earnings forecasts, scaled by stock price at the beginning of the year (Chen et al., 2015; Cui et al., 2018) as illustrated in the following equation:

$$FDispersion(X)_{i,t} = \frac{\left(\frac{1}{N} \sum_{j=1}^N SDEST_{i,j,t} \right)}{P_{i,t}} \quad (2)$$

where $SDEST_{i,j,t}$ is the standard deviation of analyst earnings forecasts in month j for firm i in year t . $P_{i,t}$ is stock price at the beginning of the year.

3.3 Climate Change Disclosure Measure

Textual analysis has been widely adopted in accounting and finance research to compute important qualitative information content of corporate reporting such as document similarity, text readability and narrative sentiment (Loughran and McDonald, 2016). Instead of analysing these generic linguistic features of text documents, we focus on firm-level climate change information disclosure by employing the TF-IDF method in textual analysis. This method was also used in Engle et al. (2020), where a market-wide climate risk exposure is computed from news articles in the *Wall Street Journal*. Specifically, the estimation process of our firm-level climate change disclosure measure involves three main steps: (1) developing a comprehensive and unique climate change vocabulary as reference for textual analysis; (2) extracting parsed and cleansed texts that are potentially relevant to climate change from firm annual reports; and (3) computing the firm-level climate change disclosure measure based on the cosine similarity between the climate change vocabulary and extracts from annual reports that are potentially related to climate change.

Based on the climate change vocabularies generated in the three steps, we obtain from step 3, the firm-level climate change similarity score (CCSS) and the four category scores corresponding to climate change Governance, Strategy, Risk Management, and Metrics & Targets (GO, ST, RM, and MT), respectively. Disclosure in each category is important. The World Economic Forum Insight Report (Schwab, 2019) indicates that climate governance by corporate boards is the foundational building block of effective climate risk and opportunity management. Practitioners often argue that the conventional corporate governance ratings are not specific to corporate environmental performance (Financial Times, 2024), highlighting the potential importance of climate governance to investors and analysts. Climate strategy lays out the long-term implications of climate risks and opportunities on corporate operations and strategic planning, which essentially reflects the strategic integration of climate disclosure into strategic decision-making processes. Climate risk management emphasizes the identification, assessment, and management of climate transition risks (risks that arise from the transition to a low-carbon economy such as policy shifts) and physical risks (risks that arise from the physical impacts of a changing climate such as increased extreme weather events), as well as commensurate opportunities if a firm has plans to mitigate these risks. This information is relevant to investors because it directly informs them of the financial implications of a firm's climate risks. Finally, climate metrics and targets provide specific targets by a firm's climate change mitigation and adaptation. As a salient example, 2,076 global firms have set their net-

zero carbon emission targets and the time horizon to achieve the targets as of 2022 based on Science-based Targets Initiative.⁸ Ioannou et al. (2016) show that setting carbon emissions reduction targets acts as an effective motivating tool for managers to attain these targets. An implication from their study is that transparent climate change targets set a clear pathway to mitigate a firm's exposure to material climate change and therefore reduce the information uncertainty of investors to assess a firm's climate risks. To further illustrate the respective information disclosure associated with each of the four subcategories, we present the TCFD recommended disclosure templates for these categories in Figure 2.

Figure 3 depicts the distribution of firm-level CCSS across countries and sectors. Panel A shows the distribution of firm-level climate disclosure intensity by countries. The boxplots are created based on the median and interquartile CCSS in each country using sample firms disclosing climate change information (i.e., CCSS > 0). France has the highest median CCSS and highest percentage (94%) of firms reporting climate change information. In contrast, the US exhibits a relatively narrow spread of climate change disclosures, with the lowest percentage (40%) of firms providing such information, which is consistent with Eccles et al. (2011) who argue that there is considerable climate change scepticism in the US.

Panel B of Figure 3 show boxplots at the sector level. Notably, high levels of climate change disclosure are evident in utilities, materials, and energy industries, with the Utilities sector exhibiting the most dispersed distribution. This aligns with the notion that these industries are more susceptible to the financial impact of climate change risks and opportunities. In contrast, the Healthcare and Information Technology industries have relatively less dispersed distribution and the lowest percentages of firms reporting climate change information, suggesting that climate change risk may be less financially material to these industries. Panel C of Figure 3 shows the distribution of climate change disclosure at category level. The highest level of climate change information is disclosed under the Metrics and Targets category, with the lowest level under the Strategy category. This finding is consistent with TCFD 2022 showing that few firms disclose the resilience of firms' strategies under different scenarios.

A detailed discussion on the estimation of these disclosure measures is provided in the Appendix, together with several validation tests on the disclosure measures. For the identification strategy, two exogenous shocks to firm-level climate change disclosures were

⁸ The information is accessed through the following weblink: <https://sciencebasedtargets.org/>.

used to determine whether our climate disclosure measure increases following regulatory reforms that mandate climate disclosures. In a difference-in-difference (DiD) setting, we find that firms with high equity ownership by French institutional investors show increased climate change disclosure scores in annual reports following Article 173 which mandated climate disclosure for both listed firms and institutional investors in France. Furthermore, climate disclosure scores for firms in France and the UK significantly increased after the passage of EU Non-Financial Reporting Directive in 2013, compared to those in Australia, Canada, and the US. Overall, we are confident that the validity of the firm-level climate change disclosure measure has been substantiated.

3.4 Research Design

Hypothesis H1 tests the relationship between firm-level aggregate climate change disclosure measured by *CCSS* and earnings forecast quality of sell-side financial analysts. Using earnings forecast error and dispersion as proxies for analyst forecast quality, we estimate the following baseline regression model:

$$Forecast(X)_{i,t+1} = \alpha + \beta CCSS_{i,t} + Y'FVEC_{i,t} + Fixed\ effects + \varepsilon_{i,t} \quad (3)$$

$Forecast(X)_{i,t+1}$ alternatively represents analyst forecast error (*FError*) or dispersion (*FDispersion*) over various (i.e., current ($X=0$), one-year ahead ($X=1$) and two-year ahead ($X=2$)) forecasting periods for firm i at $t+1$. *CCSS* is the climate change disclosure made in a financial report by firm i in year t . The list of control variables is selected following prior literature (Ben-Amar, Herrera and Martinez, 2023; Chen et al. (2015); Hope, 2003 and Dhaliwal et al., 2012), including firm size (*Size*), market-to-book ratio (*MTB*), return-on-assets ratio (*ROA*), financial leverage (*Leverage*), earnings volatility (*EarnVolatility*), earnings loss status (*EarnLoss*), carbon emissions (*CarbonEmission*), forecasting horizon (*FHorizon*), financial information opaqueness (*FinancialOpaqueness*), *ADR*, and analyst following (*#Analysts*). A detailed account of all variable definitions is provided in the Appendix. We also include year fixed effects to account for time trends, as well as country and industry fixed effects to account for time invariant country and industry characteristics. All continuous variables are winsorized at the top and bottom 2.5% of the sample distribution to alleviate the effects of extreme values. Standard errors are clustered at the firm level. We standardize all explanatory variables for all regressions analyses in this study to facilitate the interpretation of economic magnitude.

[Insert Table 2 about here]

4. Empirical Analysis

4.1 Descriptive Statistics

Table 2 provides detailed summary statistics, including means, standard deviations and medians for all non-standardized variables used in the baseline regression model. These statistics are reported for the full sample as well as for two subsamples: firms that disclose climate change information ($CCSS > 0$) and those that do not disclose climate change information ($CCSS = 0$). In the full sample, 54% of firms have climate change disclosures indicating a non-zero $CCSS$.

Panel A presents mean $CCSS$ with a value of 0.044 for the full sample and 0.081 for the subsample of firms with nonzero $CCSS$. Among the four TCFD categories, the *MT* category shows the highest level of disclosure across both the full sample and the non-zero sample, followed by *RM*, *GO*, and *ST*. This ranking indicates that firms prioritize providing specific metrics and targets related to climate change over other types of disclosures such as governance and strategy.

Panel B reveals that both the mean and standard deviation of forecast error and dispersion increase with the length of the forecasting periods. This result is consistent with prior research (Dhaliwal et al., 2012), which suggests that analysts face greater uncertainty and have less information when making predictions for longer time horizons, leading to large forecast error and greater dispersion. Notably, the differences in forecast error and dispersion between firms with zero $CCSS$ and those with nonzero $CCSS$ are insignificant, except for the $FDispersion(0)$ and $FError(2)$.

Panel C focuses on control variables and highlights significant differences between the nonzero $CCSS$ and zero $CCSS$ samples. Specifically, firms that disclose climate change information tend to be larger, more profitable, and have higher leverage compared to non-disclosing firms. These disclosing firms also generally have higher carbon emissions, broader analyst coverage, and a greater likelihood of being listed in the US. Additionally, firms with nonzero $CCSS$ exhibit lower market-to-book ratio, less earnings volatility, and fewer earnings losses, indicating greater stability in firm earnings. Furthermore, analysts tend to have shorter forecasting horizons for firms disclosing climate change information, which may reflect an enhanced predictability of firms' future performance due to greater transparency.

4.2 Main Results

Table 3 reports the estimation results for testing Hypothesis H1 based on variations of the baseline regression equation (3). In column (1), we estimate the baseline model along with all control variables as well as country, industry, and year fixed effects. The coefficient estimate of standardized *CCSS* is -0.193 (t -value = -3.78), showing that a one-standard deviation increase in *CCSS* is associated with a 0.193% decrease analyst earnings forecast error for the next year. This forecast error reduction is economically sizable. The 0.193% decrease in forecast error corresponds to 13.8% of the sample mean of $FError(0)$ (see Table 2). By comparison, [Dhaliwal et al. \(2012\)](#) show that the issuance of a stand-alone CSR report leads to a decrease in analyst forecast error by 10%. In column (2), we re-estimate the base model by replacing analyst forecast error ($FError(0)$) with forecast dispersion ($FDispersion(0)$) and find that the coefficient estimate on *CCSS* is -0.095 (t -value = -3.78). Economically, a one-standard deviation increase in *CCSS* is associated with a 0.095% decrease in $FDispersion(0)$, corresponding to 11.9% of its sample mean. This evidence suggests that material climate narratives in annual reports reduce the noise in analysts' private signals and noise in their interpretation of public signals, thereby reducing disagreement among analysts. To account for time-varying country and industry characteristics, we control for industry-year fixed effects in columns (3)-(4) and country-year fixed effects in columns (5)-(6) and find the previous findings remain qualitatively unchanged. The evidence that the magnitude of the coefficient estimates of *CCSS* remain stable across different model specifications indicates that the observed relations between *CCSS* and two forecast accuracy proxies are unlikely to pick up country- or industry-specific heterogeneities. Given the consistent results based on different combinations of fixed effects, we report our subsequent analysis by controlling for country, industry, and year fixed effects.

The estimated coefficients on control variables are consistent with our priors ([Dhaliwal et al., 2012](#); [Hope, 2003](#)). In general, forecast error and dispersion are lower in large firms, firms with high *MTB*, low *ROA*, and more *#Analysts* but greater in firms with high *Leverage*, high *EarnVolatility*, and those making *EarnLoss*. Notably, analyst forecast error and dispersion are positively associated with carbon emissions, suggesting that a firm's exposure to climate transition risk increases the information uncertainty faced by analysts, resulting in less accurate forecasts and more disagreements. This finding highlights the importance of firm-level climate disclosure in reducing the information asymmetry of financial analysts. Overall, the results in

Table 3 consistently show that aggregate climate change disclosures are negatively associated with analyst forecast errors and dispersions, providing support for Hypothesis H1.

[Insert Table 3 about here]

A unique advantage of TCFD-aligned climate disclosure is its granularity in the organisation of climate change information. Using a climate change vocabulary built on the TCFD reporting recommendations, we compute category climate disclosure scores in the following four specific aspects using the respective vocabularies: Governance, Strategy, Risk Management, and Metrics & Targets. To identify the relative importance of each disclosure dimension to analysts, we estimate the effect of each of the category scores on analyst forecast proxies. Confirming the financial materiality of TCFD categories, we observe consistently significant and negative coefficients on *GO*, *ST*, *RM*, and *MT* across all model specifications, irrespective of whether analyst forecast quality is measured by *FError(0)* (columns (1), (3), (5) and (7)) or *FDispersion(0)* (columns (2), (4), (6) and (8)). For example, the coefficient estimate of standardized *GO* is -0.142 (t -value = -3.06), denoting that a one-standard deviation increase in *GO* is associated with 0.142% decrease in current-period analyst earnings forecast error for the next year. The 0.142% decrease in forecast error corresponds to 10% of the sample mean of *FError(0)* (see Table 2). The economic magnitude of *GO* is like *RM*. Correspondingly, the coefficient estimate of standardized *ST* is -0.186 (t -value = -4.21), where that a one-standard deviation increase in *ST* results in 0.186% decrease in current-period forecast error for the next year. The 0.186% decrease in forecast error corresponds to 13.3% of the sample mean of *FError(0)* (see Table 2). In terms of economic magnitude, *ST* is like that of *MT*.

In relative terms, the coefficient estimates of *ST* and *MT* are larger in magnitude than those of *GO* and *RM*, suggestive of richer information content in climate strategy and metrics and targets disclosures. Overall, Table 4 provides convincing evidence to support H2a, H2b, H2c and H2d. The positive effects of the climate change disclosure in the four categories corroborate the previous evidence on the aggregate disclosure and substantiate the financial materiality of climate change disclosure captured by the measures.

[Insert Table 4 about here]

Further analysis at the country level shows that the main results are not driven by observations from any one country, particularly for the non-zero *CCSS* sample. We run the regression in Equation (3) for each country separately, and control for industry and year fixed effects. As shown in Table 5, the coefficients on *CCSS* and categories are negative in *FError(0)*

with 5% significance level in Australia for both the full sample (Panel A) and non-zero sample (Panel B). Interestingly, for the US sample, the estimates on *CCSS*, *ST* and *MT* are positive and significant for the full sample but insignificant for the non-zero *CCSS* sample. In contrast, the estimates on *GO* and *RM* are insignificant for the full sample, but negative and significant for the non-zero *CCSS* sample. Similar results are also found in the Panel C and D for *FDispersion(0)*. This is presumably because climate change is in general regarded with a large amount of scepticism in the US, especially over the period when Donald Trump won the 2016 US presidential election and subsequently announced the US's withdrawal from the Paris Agreement. These events resulted in little attention being paid to climate change, and therefore a lower level of disclosure among US firms. The mixed findings for the US sample are consistent with Ben-Amar et al. (2024) showing the negative association between climate risk disclosure and analyst forecast accuracy for the disclosure sample only. Dhaliwal et al. (2012) also report that US firms have limited focus on CSR engagements and disclosures, such that the issuance of CSR is not associated with forecast accuracy. In addition, we find that in the UK, the estimates on *CCSS* are negatively significant in *FError(0)* for the nonzero *CCSS* sample, and in *FDispersion(0)* for both samples, indicating a negative relationship between climate change disclosures and analyst forecast errors and dispersions and the negative effects appear stronger in *FError(0)* for the disclosure sample. Similar results are also found for other categories in the UK. In terms of Canada and France, the estimated coefficients on *CCSS* are insignificant in both *FError(0)* and *FDispersion(0)* across the full sample and nonzero *CCSS* sample, except for in *FDispersion(0)* for the full sample in Canada and France, with positive and negative significant coefficients respectively. This variation in significance and direction across five countries suggests differences in how climate change disclosures are perceived and valued by financial analysts. Overall, the UK and Australian sample exhibit stronger reactions to climate change disclosures, while in Canada, France and the US, analysts appear less sensitive and there are mixed results, possibly due to differing regulatory environments or market conditions.

[Insert Table 5 about here]

4.3 Cross-sectional Analysis

To strengthen the baseline results, we examine the heterogeneous effects of firm-disclosed climate change information across varying subsamples in additional cross-sectional analyses. First, we partition our sample into subsamples based on whether a firm is a TCFD supporter or not. TCFD supporters are more likely to disclose their climate information in alignment with

the TCFD reporting guideline, which emphasizes the financial materiality of climate information. We therefore anticipate a stronger effect of firm-disclosed climate change disclosures on analyst forecast quality for TCFD supporting companies. As the TCFD issued its final reporting guideline in June 2017, we augment the base regression model by including two dummy variables: a *TCFD Supporter* dummy equal to 1 for firms that support TCFD reporting and zero otherwise, and a *Post* dummy equal to 1 for years from 2017 and zero otherwise.

Table 6 presents the results for Hypothesis H3, examining whether the effect of aggregate climate change disclosure is more pronounced for TCFD supporters⁹. As shown in columns (1) and (2), the estimated coefficients of *TCFD Supporter*×*CCSS* in the *FError(0)* and *FDispersion(0)* regressions are negative and statistically significant, suggesting that the effect of climate change disclosures on earnings forecast quality is more pronounced among TCFD supporters. Our focus is on the three-way interaction term, *TCFD Supporter*×*Post*×*CCSS*. Column (3) shows that the coefficient estimate of *TCFD Supporter*×*Post*×*CCSS* is -0.101 (*t*-value = -3.06) in a regression with *FError(0)* as the dependent variable. The coefficient estimate remains unaffected when we replace *FError(0)* with *FDispersion(0)* in column (4).

The collective evidence suggests that climate change disclosures in alignment with the TCFD-based vocabulary adds value to investors and benefit analysts even more by providing consistent and comparable climate-related information. Additionally, credit rating agencies have reported insufficient ESG disclosures as a major obstacle for analysts when assessing a firm's creditworthiness and have urged firms to adopt TCFD recommendations for better reporting (McGrath, 2019). This implies that TCFD supporter status as a signal of disclosing fully in line with TCFD recommendations can improve a firm's credibility, which makes it easier for analysts to assess climate change information in a consistent and credible way. Accordingly, the benefits from climate change disclosures are more pronounced among TCFD supporting firms, providing evidence to support Hypothesis H3.

[Insert Table 6 about here]

⁹ We also perform the cross-sectional test using the category-level disclosure measure and find that the main results remain robust. These results are available upon request.

5. Economic Channel

In this section, we test an economic channel that may improve sell-side analysts' abilities and incentives to utilize firm-level climate disclosure. This channel centers on future financial information that may be contained in firm-level climate information disclosure. If firm-level climate change disclosure contains the future financial information associated with a firm's climate risks and opportunities, sell-side analysts can benefit from such disclosure by incorporating it into their earnings forecasts. To inspect the information content of firm-level climate disclosure, we build on [Lundholm and Myers \(2002\)](#) and [Dhaliwal et al. \(2012\)](#) and use the future earnings response coefficient to test whether current stock returns are informative of future earnings in firms with intensive climate disclosure using the following regression specification:

$$\begin{aligned}
 BHReturn_{i,t} = & \alpha + \beta_1 Earnings_{i,t-1} + \beta_2 Earnings_{i,t} + \beta_3 Earnings_{i,t+3} + \beta_4 \\
 BHReturn_{i,t+3} + & \beta_5 CCSS_{i,t} + \beta_6 CCSS_{i,t} \times Earnings_{i,t-1} + \beta_7 CCSS_{i,t} \times Earnings_{i,t} + \beta_8 \\
 CCSS_{i,t} \times & Earnings_{i,t+3} + \beta_9 CCSS_{i,t} \times BHReturn_{i,t+3} + \beta_{10} Control_{i,t} + \beta_{11} Control_{i,t} \times \\
 Earnings_{i,t-1} + & \beta_{12} Control_{i,t} \times Earnings_{i,t} + \beta_{13} Control_{i,t} \times Earnings_{i,t+3} + \beta_{14} \\
 Control_{i,t} \times & BHReturn_{i,t+3} + \varepsilon_{i,t} \quad (4)
 \end{aligned}$$

where $BHReturn_{i,t}$ is the buy-and-hold stock return over the twelve months ending four months after the end of fiscal year t for firm i . $BHReturn_{i,t+3}$ is the buy-and-hold stock return over the subsequent three years, starting from four months after the end of fiscal year t to avoid look-ahead bias. $Earnings_{i,t}$ is net income before extraordinary items divided by the market value of equity in year t for firm i , and $Earnings_{i,t+3}$ equals the sum of scaled net income before extraordinary items over three years from year $t+1$ to year $t+3$. $Control$ alternatively represents the number of analysts ($\#Analysts$), and dividend ($Dividend$) which equals one for firms that make common dividend payments following [Dhaliwal et al. \(2012\)](#). β_3 reflects the relationship between current stock returns and future earnings. Our interest lies in β_8 which shows whether and how firm-level climate change disclosure affects the relationship between current returns and future earnings.

[Insert Table 7 about here]

Column (1) of Table 7 presents the conventional regression model for estimating the returns-earnings relationship and therefore provides a benchmark for subsequent analysis. Consistent with prior literature, we find a positive and significant coefficient of $Earnings_{t+3}$, which suggests that future earnings are impounded into current stock returns. Next, we condition the regression on the firm-level climate change disclosure measure, $CCSS$. The result

in column (2) shows that the coefficient estimate of $CCSS_{i,t} \times Earnings_{t+3}$ is 0.011 (t -value = 2.13). To mitigate the confounding factors, we separately include different control variables in columns (3) and (4), respectively. Irrespective of which control variable is added to the regression, the coefficient estimate of $CCSS_{i,t} \times Earnings_{t+3}$ remains significantly positive and its magnitude hovers around 0.010. These results remain robust to the sample with nonzero $CCSS$ in columns (5) and (6). The collective evidence lends strong support that climate information disclosure in financial reports contains material information about a firm's future financial performance. Sell-side analysts utilize such material information to enhance their earnings forecast precision, thereby disseminating future earnings information into current stock prices. This finding corroborates the important information content of firm climate information disclosure.

Table 8 further present results examining how climate change disclosures at TCFD category level accelerate the incorporation of future earnings into current stock price. We find that the coefficients on $CCSS^{category} \times Earnings_{t+3}$ are positive, at 5% significance level for ST , 10% for RM , and insignificant for GO and MT . This suggests that climate change disclosures under the Strategy category facilitate a more immediate incorporation of future earnings expectations into current stock prices. This finding aligns with the notion that disclosures under the Strategy category provide direct insights into the financial implications of climate risks and opportunities on firms' operational and financial planning. Accordingly, such information is likely to be perceived by analysts as a stronger signal of a company's preparedness for climate risks and opportunities, thereby influencing stock price dynamics more rapidly.

[Insert Table 8 about here]

6. Robustness Tests

In this section, we assemble several robustness tests to substantiate the positive effect of firm-disclosed climate change information on sell-side analyst earnings forecast accuracy.

First, we consider analyst forecast bias as an alternative measure that reflects the lack of analyst forecast accuracy. The analyst forecast bias is measured by expressing mean consensus earnings forecasts minus actual earnings as a percentage of the beginning stock price where a positive value represents an optimistic earnings forecast (Das et al., 1998; Jackson, 2005; Lim, 2001). The presence of optimistic forecasts can arise from analysts' behavioral biases (Hirshleifer et al., 2021) or the need to please corporate management in exchange for private information (Das et al., 1998). The commonality across the two distinct explanations is the

limited private and public information signals analysts has about the firm under research. If disclosing climate change information helps to mitigate the information uncertainty of analysts, we expect climate disclosure to be negatively associated with analyst forecast optimism. Result in column (1) of Table 10 is consistent with our prior. We find a negative and significant coefficient of *CCSS* in the *FOptimism(0)* regression. For robustness, we also look at the effect of *CCSS* on one-year ahead and two-year ahead forecast optimism (*FOptimism(1)* and *FOptimism(2)*) in columns (2) and (3), respectively. We note that the coefficient estimates of *CCSS* become more economically significant when measuring optimism measures using alternative long-term forecasting horizons.

[Insert Table 9 about here]

Second, it is widely acknowledged in the literature that climate risks, especially climate transition risks, tend to be long term in nature (Painter, 2020; Sautner et al., 2023; Starks, 2023). Further, our material climate information captured in *CCSS* encompasses four important aspects: Governance, Strategy, Risk Management and Metrics and Targets, all of which capture in part the long-term financial ramifications of a firm's climate risks and opportunities. Hence, we anticipate the information effect of climate disclosure extends to long-term analyst forecast accuracy. To verify this conjecture, we replace current-year analyst forecast error and forecast dispersion measure with their respective one-year ahead and two-year ahead measures. In columns (4)-(7) of Table 9, we continue to observe a negative coefficient estimate of *CCSS* in regressions of *FError* and *FDispersion* over these longer-period forecasting horizons. These findings also corroborate our evidence reported in Table 8 that climate change disclosure in financial reports contains material information about future earnings.

Three, prior studies document that individual analyst characteristics, such as geographic location and personal experience of extreme weather conditions and air pollution, have a significant impact on their forecasts. For example, Cuculiza et al. (2021) find that analysts located in states with higher temperature anomalies issue more accurate earnings forecasts. Dong et al. (2021) report that air pollution gives rise to negative analyst forecast bias but this pollution effect is less pronounced for analysts located in high pollution cities. Our previous analysis is conducted at the firm-year level, masking the heterogeneity in analyst characteristics. For robustness, we repeat our analysis at the analyst level by quantifying an individual analyst's earnings forecast error as the absolute difference between the most recent earnings forecast and actual earnings, scaled by beginning-of-the-year stock price. In addition to the controls considered in our baseline model, we also include another two controls at the analyst level,

including the number of firms covered by an analyst (*#Firms*) and brokerage size (*BrokerSize*), defined as the number of analysts hired in the brokerage firm. The estimation results at the analyst level are summarized in Table 10. In line with our firm-level analysis, we observe consistently negative effects of *CCSS* on individual analyst forecast errors over three forecasting horizons and all the *CCSS* coefficient estimates are statistically significant at the 1% level. This supplementary analysis substantiates our primary findings even when analyst characteristics are accounted for.

In summary, we document a robust relationship between firm-disclosed climate change information and sell-side analyst forecast accuracy across alternative forecast accuracy measures, over alternative forecasting horizons. Our primary findings also hold in the analyst-level regression analysis.

[Insert Table 10 about here]

7. Conclusion

This study offers a novel solution to measure firm-level climate change disclosure based on its disclosure's alignment with TCFD reporting recommendations. We begin our analysis by validating our measurement through two mandatory policy reforms - Article 173 in France and EU NFR Directive – as identification strategies. These reforms exogenously augmented the demand for nonfinancial information from affected firms, providing a robust test for our measurement's effectiveness.

On the premise that sell-side financial analysts have the skills and incentives to incorporate any financially relevant information in a timely manner, we examine an important question of whether investors care about climate change disclosures by investigating the empirical relationship between firm-disclosed climate change information and analyst earnings forecast quality measured by their forecast precision and dispersion. Our results find consistent evidence that both the aggregate firm-level climate change disclosures and its four subcomponents, namely Governance, Strategy, Risk Management, and Metrics & Targets, are negatively associated with analysts' earnings forecast error and dispersion. This association is more pronounced among TCFD supporters and firms with higher exposure to climate risks. Further tests uncover a potential economic channel that can help rationalize our baseline findings. We show that stock returns tend to speed up the incorporation of future financial performance information when firms disclose their climate change information aligned with TCFD recommendations. This finding is in support of an information channel: firms tend to

report climate change disclosure in financial reports, which aids investors and analysts in interpreting the financial implications of a firm's climate risks and opportunities.

Our study focuses on the impact of firm-level climate change disclosure that aligns with the globally recognized climate disclosure framework, the TCFD, and yields significant practical implications. According to [TCFD \(2022\)](#), over 4,000 companies have voluntarily committed to implementing TCFD-aligned climate reporting in their financial reports. A growing number of jurisdictions, such as Canada and Japan, have mandated TCFD-aligned reporting in domestic regulation or are in the process of doing so. In March 2024, the US SEC mandated its climate disclosure rules with explicit references to TCFD recommendations. Globally, the ISSB has fully adopted the TCFD recommendations on climate disclosure in preparation for a global reporting framework for corporate climate change disclosures in 2021. Our findings provide important policy inputs given the widespread acceptance of TCFD recommendations as a global standard for climate disclosures. By demonstrating the financial market impact of disclosing firm-level climate change information, we underscore the positive information benefits of establishing a consistent and comparable global climate change reporting framework for global investors.

Figure 1: The Number of TCFD Supporters Across Countries

This figure shows the number of TCFD supporters across countries. TCFD supporter data is collected from the TCFD website (<https://www.fsb-tcfd.org/>). We highlight ten countries with the largest number of TCFD supporting companies from 2017, the release of TCFD recommendations, till 2019.

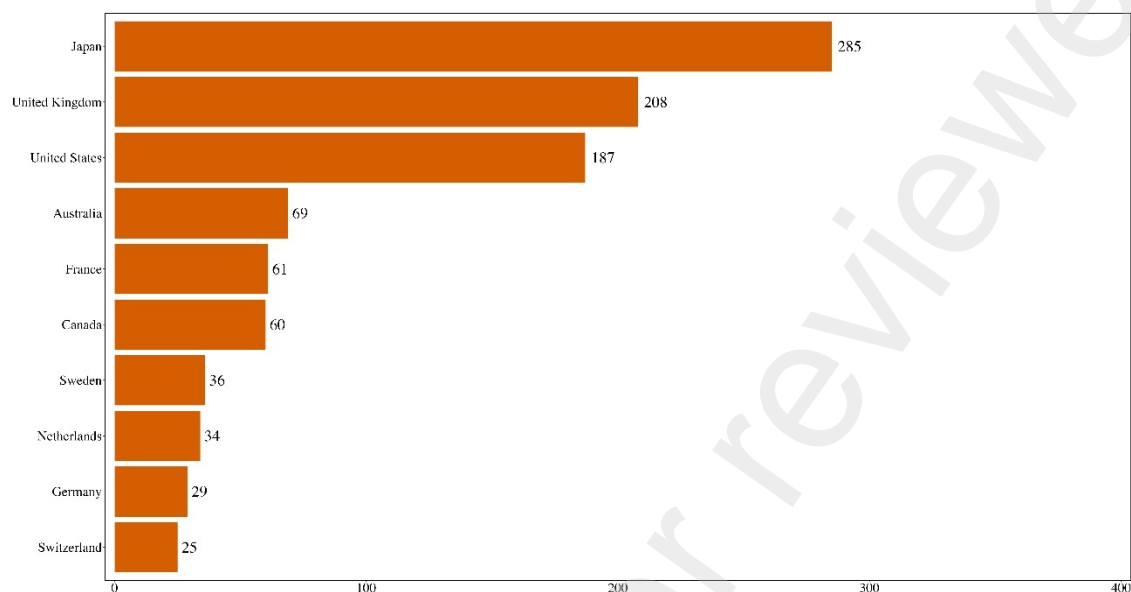


Figure 2. TCFD Recommendations for Climate Change Disclosures

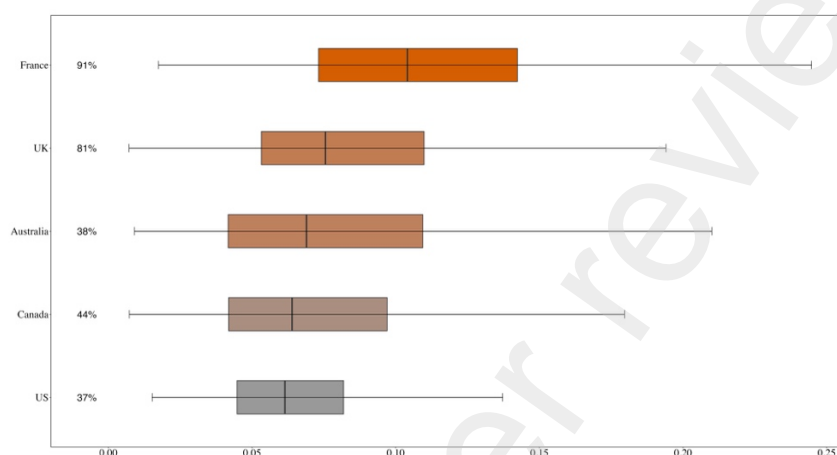
This figure is a snapshot from the TCFD website (<https://www.fsb-tcf.org/publications/>), outlining the recommended disclosure content for the four climate disclosure subcategories: climate governance, strategy, risk management, and metrics and targets.

Governance	Strategy	Risk Management	Metrics and Targets
Disclose the organization's governance around climate-related risks and opportunities.	Disclose the actual and potential impacts of climate-related risks and opportunities on the organization's businesses, strategy, and financial planning where such information is material.	Disclose how the organization identifies, assesses, and manages climate-related risks.	Disclose the metrics and targets used to assess and manage relevant climate-related risks and opportunities where such information is material.
Recommended Disclosures	Recommended Disclosures	Recommended Disclosures	Recommended Disclosures
a) Describe the board's oversight of climate-related risks and opportunities.	a) Describe the climate-related risks and opportunities the organization has identified over the short, medium, and long term.	a) Describe the organization's processes for identifying and assessing climate-related risks.	a) Disclose the metrics used by the organization to assess climate-related risks and opportunities in line with its strategy and risk management process.
b) Describe management's role in assessing and managing climate-related risks and opportunities.	b) Describe the impact of climate-related risks and opportunities on the organization's businesses, strategy, and financial planning.	b) Describe the organization's processes for managing climate-related risks.	b) Disclose Scope 1, Scope 2, and, if appropriate, Scope 3 greenhouse gas (GHG) emissions, and the related risks.
	c) Describe the resilience of the organization's strategy, taking into consideration different climate-related scenarios, including a 2°C or lower scenario.	c) Describe how processes for identifying, assessing, and managing climate-related risks are integrated into the organization's overall risk management.	c) Describe the targets used by the organization to manage climate-related risks and opportunities and performance against targets.

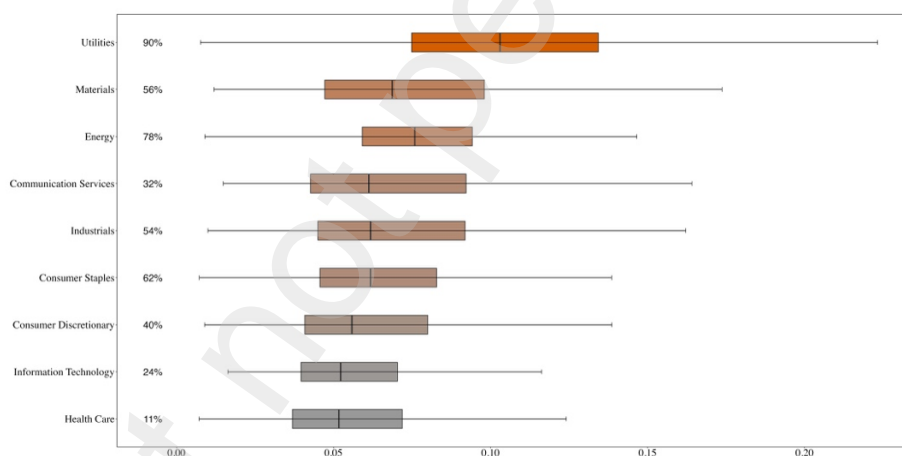
Figure 3: Firm-level Climate Change Disclosure Distribution

This figure shows the distribution of climate change similarity scores (CCSS) across countries in Panel A, industries in Panel B and TCFD categories in Panel C. CCSS is the measure of firm-level climate change disclosures. The boxplots display the percentage of firms disclosing climate change information in annual reports on a sample of firms with non-negative CCSS. The left and right ends of the box denote the 25th and 75th percentiles of CCSS, respectively, and the vertical line inside the box denotes its median value. The left and right whiskers outside the box represent the CCSS values corresponding to 1.5 times the 25th and 75th percentiles, respectively. The countries and sectors are ranked based on the average value of CCSS.

Panel A: Climate change disclosures across countries



Panel B: Climate change disclosures across sectors



Panel C: Climate change disclosures across categories

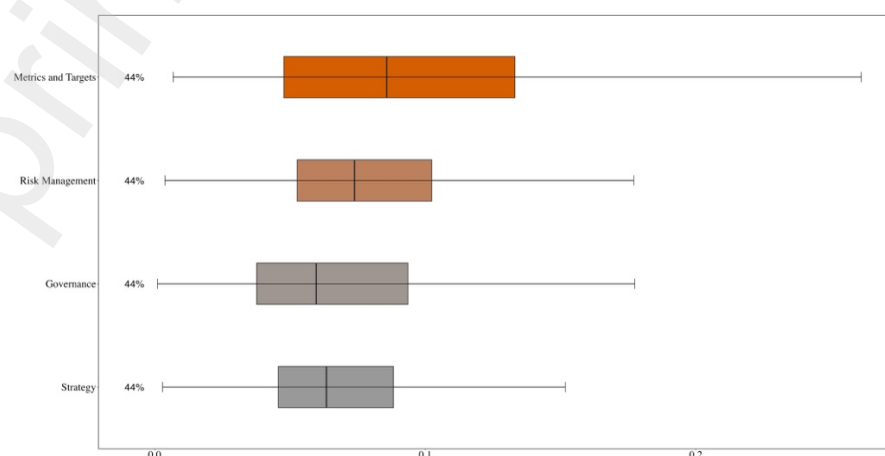


Table 1: Sample Formation

This table shows sample formation in each country. The initial sample consists of all unique firms from the largest 300 companies in Australia, 350 companies in the UK, 150 companies in France, 300 companies in Canada, and 3000 companies in the US in each year between 2010 and 2019. For each firm, we collect annual reports over the period from 2010 to 2019. We omit financial firms with SIC classification between 6000 and 6999. Then we delete firms with negative book equity after merging with I/B/E/S, Compustat, CRSP and the LSEG databases, generating a final sample with 16,926 non-missing firm-year observations.

Data Filters	Full Sample		Australia		Canada		France		UK		USA	
	Obs	Firms	Obs	Firms	Obs	Firms	Obs	Firms	Obs	Firms	Obs	Firms
Initial sample	50,089	6,870	4,990	656	4,597	581	1,646	197	5,333	655	33,523	4,781
Sample after excluding financial firms	38,052	5,333	3,879	511	3,715	479	1,371	162	3,666	456	25,421	3,725
Sample after merging with Compustat, IBES and LSEG ESG	17,489	3,110	1,917	318	1,767	275	843	117	2,190	307	10,772	2,093
Sample after deleting firm-year observations with negative book equity values	16,926	3,057	1,912	316	1,751	274	823	115	2,146	306	10,294	2,046

Table 2: Summary Statistics

This table reports the mean and standard deviation (St.Dev) values of dependent variables and independent variables in Panels A and B, respectively, for the full sample and each country-specific subsample. The dependent variables are analyst forecast error (*FError*) and dispersion (*FDispersion*) over different forecasting periods with 0/1/2 representing the current, one-year, and two-year ahead forecasting periods. The main independent variables include the aggregate firm-level climate change similarity score (*CCSS*), and its four subcomponents, namely, the climate governance score (*GO*), strategy score (*ST*), risk management score (*RM*) and metrics and targets score (*MT*). The list of control variables in the main regression includes firm size (*Size*), market-to-book ratio (*MTB*), return on assets (*ROA*), leverage ratio (*Leverage*), earnings volatility (*EarnVolatility*), earnings loss indicator (*EarnLoss*), carbon emissions (*CarbonEmission*), forecasting horizon (*FHorizon*), and the number of analysts (*#Analysts*). All variables are defined in the Appendix.

	Full Sample (Obs=16,926)			CCSS>0 (Obs=9,117)			CCSS=0 (Obs=7,809)			Difference in Mean	
Panel A: Main Variables	Mean	St.Dev	Median	Mean	St.Dev	Median	Mean	St.Dev	Median	<i>Difference</i>	<i>p-value</i>
CCSS	0.044	0.052	0.034	0.081	0.044	0.071	0	0	0		
- Governance (<i>GO</i>)	0.045	0.061	0.025	0.083	0.061	0.068	0	0	0		
- Strategy (<i>ST</i>)	0.042	0.052	0.032	0.078	0.047	0.067	0	0	0		
- Risk Management (<i>RM</i>)	0.049	0.060	0.035	0.090	0.055	0.078	0	0	0		
- Metrics and Targets (<i>MT</i>)	0.057	0.072	0.026	0.106	0.067	0.094	0	0	0		
Panel B: Dependent Variables											
FError0	0.014	0.029	0.005	0.015	0.029	0.005	0.014	0.030	0.005	0.001	0.213
FDispersion0	0.008	0.014	0.003	0.008	0.014	0.003	0.007	0.015	0.002	0.001	0.010
FError1	0.033	0.063	0.011	0.034	0.063	0.012	0.032	0.063	0.011	0.002	0.112
FDispersion1	0.012	0.021	0.004	0.012	0.020	0.005	0.012	0.023	0.004	0.000	0.546
FError2	0.047	0.099	0.015	0.049	0.101	0.016	0.045	0.095	0.014	0.005	0.014
FDispersion2	0.015	0.027	0.006	0.015	0.027	0.006	0.014	0.029	0.005	0.001	0.406
Panel C: Control Variables											
Size	21.791	1.584	21.761	22.304	1.453	22.281	21.193	1.520	21.177	1.111	0.000
MTB	3.638	3.921	2.350	3.004	3.284	1.976	4.379	4.441	2.891	-1.375	0.000
ROA	0.029	0.116	0.044	0.040	0.079	0.043	0.015	0.147	0.046	0.025	0.000
Leverage	0.246	0.170	0.241	0.271	0.159	0.266	0.217	0.178	0.202	0.054	0.000
EarnVolatility	-1.143	1.325	-1.014	-1.210	1.395	-1.081	-1.066	1.233	-0.944	-0.144	0.000
EarnLoss	0.120	0.326	0.000	0.082	0.274	0.000	0.166	0.372	0.000	-0.084	0.000
CarbonEmission	11.816	2.689	11.661	12.920	2.557	12.719	10.526	2.225	10.601	2.395	0.000
FHorizon	91.769	41.844	97.000	86.276	43.198	91.000	98.182	39.246	99.000	-11.905	0.000
FinancialOpaqueness	0.278	0.448	0.000	0.287	0.453	0.000	0.268	0.443	0.000	0.020	0.004
ADR	0.015	0.123	0.000	0.025	0.155	0.000	0.005	0.067	0.000	0.020	0.000
#Analysts	2.259	0.733	2.398	2.386	0.679	2.485	2.109	0.765	2.197	0.277	0.000

Table 3: Climate Change Disclosure and Analyst Forecasts Quality

This table reports the regression results of analyst earnings forecast quality on firm-level climate change disclosure, controlling for other firm characteristics. $FError(0)_{t+1}$ and $FDispersion(0)_{t+1}$ represent analyst forecast error and dispersion over the current period at $t+1$, respectively. $CCSS$ is the aggregate climate change disclosure variable. The list of control variables includes firm size ($Size$), market-to-book ratio (MTB), return on assets (ROA), financial leverage ratio ($Leverage$), earnings volatility ($EarnVolatility$), earnings loss indicator ($EarnLoss$), carbon emissions ($CarbonEmission$), forecasting horizon ($FHorizon$), financial information opaqueness ($FinancialOpaqueness$), ADR, and the number of analysts ($\#Analysts$). All variables are defined in the Appendix. The regression models also include a combination of country, industry and year fixed effects. The t -statistics in parentheses are adjusted for standard errors clustered at the firm level. All coefficient estimates are multiplied by 100. *, **, *** represent the 10%, 5% and 1% significance level, respectively.

	FError(0) _{t+1} [1]	FDispersion(0) _{t+1} [2]	FError(0) _{t+1} [3]	FDispersion(0) _{t+1} [4]	FError(0) _{t+1} [5]	FDispersion(0) _{t+1} [6]
$CCSS_t$	-0.193*** (-3.78)	-0.095*** (-3.92)	-0.230*** (-4.24)	-0.115*** (-4.44)	-0.185*** (-3.46)	-0.089*** (-3.47)
$Size_t$	-0.453*** (-6.19)	-0.228*** (-6.17)	-0.429*** (-5.77)	-0.200*** (-5.31)	-0.416*** (-5.84)	-0.209*** (-5.74)
MTB_t	-0.429*** (-14.39)	-0.208*** (-15.32)	-0.378*** (-13.38)	-0.178*** (-13.72)	-0.399*** (-13.97)	-0.193*** (-14.77)
ROA_t	-0.310*** (-6.81)	-0.206*** (-9.68)	-0.287*** (-6.18)	-0.185*** (-8.81)	-0.302*** (-6.83)	-0.202*** (-9.83)
$Leverage_t$	0.346*** (9.15)	0.169*** (9.43)	0.324*** (8.46)	0.160*** (8.76)	0.335*** (8.95)	0.163*** (9.09)
$EarnVolatility_t$	0.412*** (8.39)	0.180*** (8.11)	0.406*** (7.82)	0.167*** (7.24)	0.414*** (8.43)	0.179*** (8.06)
$EarnLoss_t$	0.498*** (9.76)	0.263*** (11.25)	0.544*** (10.15)	0.281*** (11.64)	0.495*** (9.90)	0.260*** (11.34)
$CarbonEmission_t$	0.428*** (5.99)	0.171*** (4.35)	0.427*** (5.69)	0.160*** (3.86)	0.401*** (5.70)	0.159*** (4.03)
$FHorizon_t$	0.028 (0.90)	0.027* (1.75)	0.036 (1.09)	0.031* (1.82)	0.024 (0.80)	0.023 (1.51)
$FinancialOpaqueness_t$	-0.019 (-0.76)	0.00002 (0.00)	-0.035 (-1.29)	-0.007 (-0.53)	-0.016 (-0.66)	0.002 (0.13)
ADR_t	-0.044 (-1.05)	-0.031 (-1.37)	-0.047 (-1.13)	-0.032 (-1.41)	-0.044 (-1.06)	-0.032 (-1.38)
$\#Analysts_t$	-0.407*** (-9.06)	-0.130*** (-6.52)	-0.422*** (-9.19)	-0.148*** (-7.19)	-0.439*** (-9.91)	-0.147*** (-7.46)
Adjusted R2	0.29	0.43	0.27	0.42	0.30	0.45
Observations	16,926	16,926	16,926	16,926	16,926	16,926
Country FE	Yes	Yes	Yes	Yes	No	No
Industry FE	Yes	Yes	No	No	Yes	Yes
Year FE	Yes	Yes	No	No	No	No
Country*Year FE	No	No	No	No	Yes	Yes
Industry*Year FE	No	No	Yes	Yes	No	No

Table 4: Climate Disclosure Categories and Analyst Forecasts

This table presents the results of analyst forecast error and dispersion on each of the four category-level climate disclosure scores. The main variables of interest are individual disclosure scores under four TCFD reporting pillars, namely, governance (*GO*), strategy (*ST*), risk management (*RM*) and metrics and targets (*MT*). $FError(0)_{t+1}$ and $FDispersion(0)_{t+1}$ denote analyst forecast error and dispersion over the current period at $t+1$. Control variables are firm size (*Size*), market-to-book ratio (*MTB*), return on assets (*ROA*), leverage ratio (*Leverage*), earnings volatility (*EarnVolatility*), earnings loss status (*EarnLoss*), carbon emissions (*CarbonEmission*), forecasting horizon (*FHorizon*), financial information opaqueness (*FinancialOpaqueness*), ADR, and the number of analysts (*#Analysts*). All variables are defined in Appendix. The t -statistics in parentheses are adjusted by standard errors clustered at the firm level. All coefficient estimates are multiplied by 100. *, **, *** represent the 10%, 5% and 1% significance level, respectively.

	$FError(0)_{t+1}$ [1]	$FDispersion(0)_{t+1}$ [2]	$FError(0)_{t+1}$ [3]	$FDispersion(0)_{t+1}$ [4]	$FError(0)_{t+1}$ [5]	$FDispersion(0)_{t+1}$ [6]	$FError(0)_{t+1}$ [7]	$FDispersion(0)_{t+1}$ [8]
GO_t	-0.142*** (-3.06)	-0.068*** (-3.14)						
ST_t			-0.186*** (-4.21)	-0.091*** (-4.22)				
RM_t					-0.138*** (-2.73)	-0.070*** (-2.89)		
MT_t							-0.183*** (-3.72)	-0.100*** (-4.43)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,926	16,926	16,926	16,926	16,926	16,926	16,926	16,926
Adjusted R2	0.29	0.43	0.29	0.43	0.29	0.43	0.29	0.43

Table 5: Country-by-Country Examination

This table presents the estimated coefficients on CCSS and each of the four category-level climate disclosure scores for each country. The dependent variables are $FError(0)_{t+1}$ and $FDispersion(0)_{t+1}$, denoting analyst forecast error and dispersion over the current period at $t+1$. Control variables are firm size (*Size*), market-to-book ratio (*MTB*), return on assets (*ROA*), leverage ratio (*Leverage*), earnings volatility (*EarnVolatility*), earnings loss status (*EarnLoss*), carbon emissions (*CarbonEmission*), forecasting horizon (*FHorizon*), financial information opaqueness (*FinancialOpaqueness*), ADR, and the number of analysts (*#Analysts*). The *t*-statistics in parentheses are adjusted by standard errors clustered at the firm level. All coefficient estimates are multiplied by 100. *, **, *** represent the 10%, 5% and 1% significance levels, respectively.

	CCSS	GO	ST	RM	MT	Obs
Dependent Variable = FError(0)						
Panel A: Full Sample						
Australia	-0.163(-2.26)**	-0.188(-3.18)***	-0.169(-2.55)**	-0.198(-3.13)***	-0.076(-1.17)	1912
Canada	0.000(0.00)	0.022(0.26)	0.007(0.07)	0.075(0.94)	-0.014(-0.17)	1751
France	-0.010(-0.11)	-0.098(-1.29)	0.069(0.80)	0.088(0.96)	-0.093(-1.22)	823
UK	-0.059(-1.16)	-0.045(-1.12)	-0.051(-1.18)	-0.076(-1.67)*	0.018(0.48)	2146
US	0.064(2.77)***	0.022(1.20)	0.061(2.77)***	0.029(1.34)	0.070(2.79)***	10294
Panel B: CCSS > 0						
Australia	-0.249(-2.41)**	-0.279(-3.26)***	-0.241(-2.46)**	-0.311(-3.52)***	-0.085(-1.09)	919
Canada	-0.081(-0.69)	-0.038(-0.35)	-0.032(-0.28)	0.046(0.47)	-0.063(-0.56)	928
France	0.005(0.05)	-0.094(-1.16)	0.086(1.00)	0.114(1.29)	-0.090(-1.19)	786
UK	-0.115(-2.12)**	-0.083(-1.98)**	-0.091(-2.04)**	-0.113(-2.38)**	-0.020(-0.48)	1951
US	-0.027(-0.74)	-0.054(-2.24)**	-0.017(-0.55)	-0.071(-2.47)**	-0.006(-0.16)	4533
Dependent Variable = FDispersion(0)						
Panel C: Full Sample						
Australia	-0.060(-1.53)	-0.081(-2.47)**	-0.054(-1.52)	-0.084(-2.29)**	-0.007(-0.18)	1912
Canada	0.076(1.94)*	0.055(1.59)	0.087(2.19)**	0.088(2.47)**	0.051(1.47)	1751
France	-0.071(-2.12)**	-0.075(-3.12)***	-0.005(-0.14)	-0.037(-1.26)	-0.070(-1.93)*	823
UK	-0.053(-1.89)*	-0.042(-1.97)**	-0.043(-1.77)*	-0.046(-1.83)*	-0.016(-0.82)	2146
US	0.031(2.89)***	0.009(1.05)	0.026(2.46)**	0.012(1.17)	0.038(3.25)***	10294
Panel D: CCSS > 0						
Australia	-0.075(-1.52)	-0.111(-2.57)**	-0.062(-1.31)	-0.126(-2.48)**	0.006(0.15)	919
Canada	0.061(1.20)	0.023(0.55)	0.096(2.07)**	0.078(1.79)*	0.028(0.59)	928
France	-0.028(-0.88)	-0.053(-1.97)**	0.039(1.10)	0.001(0.03)	-0.033(-1.04)	786
UK	-0.071(-2.33)**	-0.055(-2.44)**	-0.053(-2.14)**	-0.057(-2.19)**	-0.025(-1.23)	1951
US	-0.001(-0.06)	-0.021(-1.89)*	-0.006(-0.44)	-0.031(-2.23)**	0.010(0.62)	4533

Table 6: Firm-level Climate Disclosure Following the Launch of TCFD Recommendations

This table reports the regressions examining the effects of firm-level climate disclosure on analyst forecast quality following the launch of TCFD recommendations in 2017. $FError(0)_{t+1}$ and $FDispersion(0)_{t+1}$ denote analyst forecast error and dispersion over the current periods at $t+1$, respectively. *TCFD Supporter* is a dummy variable which equals one if the firm is a TCFD supporter, and zero otherwise. *CCSS* is the aggregate TCFD-aligned climate change disclosure at the firm level. *Post* is a dummy variable, which is equal to one for firm-year observations after June 2017. Control variables are firm size (*Size*), market-to-book ratio (*MTB*), return on assets (*ROA*), leverage ratio (*Leverage*) earnings volatility (*EarnVolatility*), earnings loss indicator (*EarnLoss*), carbon emissions (*CarbonEmission*), forecasting horizon (*FHorizon*), financial information opaqueness (*FinancialOpaqueness*), ADR, and the number of analysts (*#Analysts*). Country, industry and year fixed effects are included. All variables are defined in the Appendix. The *t*-statistics in parentheses are adjusted by standard errors clustered at the firm level. All coefficient estimates are multiplied by 100. *, **, *** represent the 10%, 5% and 1% significance level, respectively.

	$FError(0)_{t+1}$ [1]	$FDispersion(0)_{t+1}$ [2]	$FError(0)_{t+1}$ [3]	$FDispersion(0)_{t+1}$ [4]
TCFD Supporter*CCSS _{<i>t</i>}	-0.153*** (-3.11)	-0.065** (-2.51)	-0.081 (-1.34)	-0.036 (-1.08)
TCFD Supporter*Post _{<i>t</i>}			0.025 (0.86)	0.019 (1.46)
CCSS*Post _{<i>t</i>}			0.166*** (4.12)	0.091*** (4.80)
TCFD Supporter*Post*CCSS _{<i>t</i>}			-0.101*** (-3.06)	-0.048*** (-2.83)
TCFD Supporter _{<i>t</i>}	0.044 (1.16)	0.017 (0.86)	0.018 (0.43)	0.007 (0.30)
CCSS _{<i>t</i>}	-0.153*** (-2.93)	-0.078*** (-3.17)	-0.250*** (-4.42)	-0.131*** (-4.41)
Control _{<i>t</i>}	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	16,926	16,926	16,926	16,926
Adjusted R2	0.29	0.43	0.29	0.43

Table 7: The Effects of Climate Change Disclosure on the Return-Earnings Relationship

The table presents the regression results of climate change disclosure on the current stock return-earnings relation. The dependent variable, $BHReturn_t$, is the buy-hold stock return over the twelve-month period ending four months after the end of fiscal year t . $BHReturn_{t+3}$ is the buy-hold stock return over the subsequent three years starting from four months after the end of fiscal year t . $Earnings_t$ is net income before extraordinary items divided by the market value of equity in year t , and $Earnings_{t+3}$ equals the sum of scaled net income before extraordinary items for the three years following year t . Control variables (*Control*) are the number of analysts ($\#Analysts$) and dividend indicator (*Dividend*) which is equal to one if a firm has common dividend payment, and zero otherwise. All variables are defined in the Appendix. The t -statistics in parentheses are adjusted by robust standard errors. *, **, *** represent the 10%, 5% and 1% significance level, respectively.

Dependent Variable: $BHReturn_t$			Control = $\#Analysts$	Control = <i>Dividend</i>
	[1]	[2]	[3]	[4]
$Earnings_{t-1}$	-0.071*** (-15.55)	-0.081*** (-12.62)	-0.106*** (-8.79)	-0.087*** (-12.15)
$Earnings_t$	0.070*** (19.01)	0.082*** (15.76)	0.097*** (9.28)	0.090*** (14.71)
$Earnings_{t+3}$	0.084*** (20.26)	0.077*** (13.99)	0.078*** (6.62)	0.082*** (12.54)
$BHReturn_{t+3}$	-0.033*** (-8.82)	-0.022*** (-4.71)	-0.083*** (-8.13)	-0.024*** (-4.18)
$CCSS_t$		-0.028*** (-8.06)	-0.024*** (-6.95)	-0.025*** (-7.40)
$CCSS * Earnings_{t-1}$		0.019*** (3.44)	0.016*** (2.81)	0.016*** (2.75)
$CCSS * Earnings_t$		-0.018*** (-3.71)	-0.015*** (-3.07)	-0.017*** (-3.43)
$CCSS * Earnings_{t+3}$		0.011** (2.13)	0.010** (2.00)	0.012** (2.25)
$CCSS * BHReturn_{t+3}$		-0.025*** (-5.63)	-0.029*** (-6.72)	-0.025*** (-5.64)
$Control_t$			-0.016*** (-3.97)	-0.015*** (-3.77)
$Control * Earnings_{t-1}$			0.030*** (2.72)	0.017*** (3.46)
$Control * Earnings_t$			-0.020** (-2.01)	-0.012*** (-3.04)
$Control * Earnings_{t+3}$			0.001 (0.06)	-0.006 (-1.15)
$Control * BHReturn_{t+3}$			0.070*** (7.19)	0.001 (0.24)
Observations	15,058	15,058	15,058	15,058
Adjusted R2	0.10	0.11	0.11	0.11

Table 8: The Effects of Category-level Disclosures on the Return-Earnings Relationship

The table presents the regression results of category-level climate change disclosure on the current stock return-earnings relation. The dependent variable, $BHReturn_t$, is the buy-hold stock return over the twelve-month period ending four months after the end of fiscal year t . $BHReturn_{t+3}$ is the buy-hold stock return over the subsequent three years starting from four months after the end of fiscal year t . Control variables (*Control*) are the number of analysts (*#Analysts*) and dividend indicator (*Dividend*) which is equal to one if a firm has common dividend payment, and zero otherwise. The t -statistics in parentheses are adjusted by robust standard errors. *, **, *** represent the 10%, 5% and 1% significance level, respectively.

Dependent Variable: $BHReturn_t$	Control = #Analysts	Control = Dividend	Control = #Analysts	Control = Dividend	Control = #Analysts	Control = Dividend	Control = #Analysts	Control = Dividend
	GO [1]	GO [2]	ST [3]	ST [4]	RM [5]	RM [6]	MT [7]	MT [8]
$Earning_{t-1}$	-0.105*** (-8.68)	-0.086*** (-12.16)	-0.105*** (-8.71)	-0.087*** (-12.07)	-0.107*** (-8.70)	-0.086*** (-11.83)	-0.104*** (-8.82)	-0.089*** (-12.76)
$Earning_t$	0.098*** (9.34)	0.088*** (14.70)	0.097*** (9.27)	0.089*** (14.52)	0.098*** (9.23)	0.088*** (14.38)	0.096*** (9.30)	0.089*** (15.15)
$Earning_{t+3}$	0.079*** (6.61)	0.085*** (13.19)	0.078*** (6.65)	0.082*** (12.57)	0.078*** (6.58)	0.083*** (12.77)	0.080*** (6.82)	0.086*** (13.49)
$BHReturn_{t+3}$	-0.084*** (-8.13)	-0.025*** (-4.40)	-0.082*** (-7.95)	-0.023*** (-4.00)	-0.082*** (-7.98)	-0.024*** (-4.17)	-0.085*** (-8.34)	-0.025*** (-4.47)
$CCSS_{Category_t}$	-0.019*** (-5.46)	-0.020*** (-5.60)	-0.023*** (-6.53)	-0.024*** (-6.81)	-0.022*** (-6.40)	-0.023*** (-6.54)	-0.021*** (-6.20)	-0.023*** (-6.70)
$CCSS_{Category} * Earning_{t-1}$	0.012** (2.02)	0.011* (1.87)	0.015** (2.49)	0.015** (2.44)	0.012** (1.98)	0.011* (1.77)	0.019*** (3.82)	0.019*** (3.68)
$CCSS_{Category} * Earning_t$	-0.013*** (-2.69)	-0.014*** (-3.00)	-0.014*** (-2.82)	-0.016*** (-3.13)	-0.012** (-2.47)	-0.013*** (-2.64)	-0.014*** (-3.27)	-0.016*** (-3.73)
$CCSS_{Category} * Earning_{t+3}$	0.004 (0.89)	0.006 (1.26)	0.011** (1.98)	0.012** (2.26)	0.008 (1.54)	0.010* (1.82)	0.001 (0.20)	0.003 (0.58)
$CCSS_{Category} * BHReturn_{t+3}$	-0.026*** (-5.66)	-0.023*** (-4.93)	-0.030*** (-6.80)	-0.026*** (-5.85)	-0.028*** (-5.98)	-0.024*** (-5.11)	-0.028*** (-6.79)	-0.023*** (-5.63)
$Control_t$	-0.017*** (-4.31)	-0.015*** (-3.89)	-0.017*** (-4.12)	-0.013*** (-3.44)	-0.017*** (-4.24)	-0.014*** (-3.56)	-0.017*** (-4.14)	-0.015*** (-3.75)
$Control * Earning_{t-1}$	0.032*** (2.86)	0.019*** (3.76)	0.030*** (2.73)	0.018*** (3.50)	0.033*** (2.98)	0.019*** (3.66)	0.026** (2.35)	0.016*** (3.23)
$Control * Earning_t$	-0.023** (-2.35)	-0.012*** (-2.94)	-0.020** (-2.09)	-0.012*** (-2.96)	-0.022** (-2.30)	-0.012*** (-3.00)	-0.019* (-1.95)	-0.012*** (-2.93)
$Control * Earning_{t+3}$	0.004 (0.34)	-0.006 (-1.08)	0.0003 (0.03)	-0.006 (-1.18)	0.002 (0.17)	-0.006 (-1.18)	0.004 (0.34)	-0.005 (-1.01)
$Control * BHReturn_{t+3}$	0.069*** (7.05)	0.001 (0.24)	0.069*** (7.17)	0.002 (0.41)	0.069*** (7.08)	0.001 (0.32)	0.070*** (7.23)	0.001 (0.22)
Observations	15,058	15,058	15,058	15,058	15,058	15,058	15,058	15,058
Adjusted R2	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11

Table 9: Robustness Checks

This table reports several robustness test results. $FOptimism(0)_{t+1}$ is analyst forecast bias over current forecasting year at year $t+1$, calculated as mean earnings forecasts minus actual earnings as a percentage of the beginning-of-the-year stock price. $FOptimism(1)_{t+1}$ and $FOptimism(2)_{t+1}$ denote analyst forecast bias over one- and two-year ahead forecasting periods at year $t+1$, respectively. $FError(1)_{t+1}$ and $FError(2)_{t+1}$ denote analyst forecast errors over the one- and two-year ahead forecasting periods at year $t+1$. $FDispersion(1)_{t+1}$ and $FDispersion(2)_{t+1}$ denote analyst forecast dispersions over the one- and two-year ahead forecasting periods at year $t+1$. Control variables are firm size (*Size*), market-to-book ratio (*MTB*), return on assets (*ROA*), leverage ratio (*Leverage*), earnings volatility (*EarnVolatility*), earnings loss indicator (*EarnLoss*), carbon emissions (*CarbonEmission*), forecasting horizon (*FHorizon*), financial information opaqueness (*FinancialOpaqueness*), ADR, and the number of analysts (*#Analysts*). All variables are defined in the Appendix. The *t*-statistics in parentheses are adjusted by standard errors clustered at the firm level. All coefficient estimates are multiplied by 100. *, **, *** represent the 10%, 5% and 1% significance level, respectively.

	FOptimistic(0) _{t+1}	FOptimistic(1) _{t+1}	FOptimistic(2) _{t+1}	FError(1) _{t+1}	FError(2) _{t+1}	FDispersion(1) _{t+1}	FDispersion(2) _{t+1}
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
CCSS _t	-0.098*** (-2.60)	-0.358*** (-3.12)	-0.465** (-2.11)	-0.450*** (-3.93)	-0.578*** (-2.66)	-0.142*** (-3.39)	-0.169** (-2.54)
Control _t	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,926	13,810	10,047	13,810	10,047	13,810	10,047
Adjusted R2	0.07	0.16	0.20	0.26	0.25	0.44	0.41

Table 10: Analyst-level Analysis

This table reports the regression results of individual analyst forecast errors over different forecasting horizons on firm-level climate change disclosure measure, *CCSS*, at the analyst level. In addition to the list of control variables used in Table 6, we also include additional analyst-level variables, including the number for firms covered by an analyst (*#Firms*; calculated as the natural logarithm of the number of firms covered by an analyst in a given year), and the size of an analyst's brokerage firm (*Broker Size*; calculated as the natural logarithm of the number of analysts in a brokerage company). Country, industry, year and analyst fixed effects are controlled. All variables are defined in the Appendix. The *t-statistics* in parentheses are adjusted by standard errors clustered at the firm level. All coefficient estimates are multiplied by 100. *, **, *** represent the 10%, 5% and 1% significance level, respectively.

	FError(0) _{t+1}	FError(1) _{t+1}	FError(2) _{t+1}
CCSS _t	-0.053*** (-3.14)	-0.257*** (-3.97)	-0.329** (-2.54)
Size _t	-0.054** (-2.34)	-0.373*** (-4.34)	-0.624*** (-3.77)
MTB _t	-0.119*** (-12.11)	-0.399*** (-10.49)	-0.483*** (-7.35)
ROA _t	-0.091*** (-6.73)	-0.239*** (-5.34)	-0.259** (-2.54)
Leverage _t	0.103*** (8.58)	0.320*** (6.49)	0.406*** (4.18)
EarnVolatility _t	0.094*** (6.68)	0.346*** (6.17)	0.609*** (5.01)
EarnLoss _t	0.154*** (9.66)	0.254*** (4.47)	0.245** (2.25)
CarbonEmission _t	0.065*** (3.00)	0.335*** (3.87)	0.251 (1.41)
FHorizon _t	0.137*** (23.39)	0.254*** (14.48)	0.250*** (7.93)
FinancialOpaqueness _t	0.007 (0.94)	0.013 (0.44)	0.072 (1.16)
ADR _t	-0.045** (-2.25)	-0.117* (-1.80)	-0.294** (-2.19)
#Analysts _t	-0.200*** (-13.51)	-0.517*** (-9.72)	-0.628*** (-5.66)
#Firms _t	-0.044*** (-4.50)	-0.068** (-2.44)	-0.116** (-2.08)
BrokerSize _t	0.001 (0.11)	0.003 (0.09)	0.095 (1.21)
Country FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes
Observations	208,732	152,019	75,673
Adjusted R2	0.33	0.34	0.37

Appendix: Variables Definitions

Variables	Description
<i>Analyst Forecasting Variables</i>	
FError (0/1/2)	A firm's analyst forecast error at year t for current year (t), one year ahead (t+1) and two year ahead (t+2). The analyst forecast error is measured as the average monthly value of the absolute difference between analyst mean estimates and actual earnings, then scaled by stock price at the beginning of the year. (I/B/E/S summary)
FDispersion (0/1/2)	A firm's analyst forecast deviation from the expected earnings at year t for current year (t), one year ahead (t+1) and two year ahead (t+2). The forecast dispersion is calculated as the average monthly standard deviation of analyst estimates, then scaled by stock price at the beginning of the year. (I/B/E/S summary)
FOptimism (0/1/2)	A firm's analyst forecast bias from the actual earnings at year t for current year (t), one year ahead (t+1) and two year ahead (t+2). The forecast optimism is calculated as mean earnings forecasts minus actual earnings, then scaled by stock price at the beginning of the year. (I/B/E/S summary)
<i>Climate Change Disclosure Variables</i>	
CCSS	Aggregate Climate Change Similarity Score, computed as the cosine similarity between a firm's climate disclosure in its annual financial report and a fixed climate change vocabulary constructed in alignment with TCFD reporting framework. (LSEG Workspace)
GO	Climate change similarity score for the Governance category of the TCFD reporting framework. (LSEG Workspace)
ST	Climate change similarity score for the Strategy category of the TCFD reporting framework. (LSEG Workspace)
RM	Climate change similarity score for the Risk Management category of the TCFD reporting framework. (LSEG Workspace)
MT	Climate change similarity score for the Metrics and Targets category of the TCFD reporting framework. (LSEG Workspace)
<i>Control Variables</i>	
Size	Natural logarithm of a firm's total assets in US dollars in a given year. (Compustat)
MTB	Market-to-book ratio, calculated as the market value of equity divided by the book value of equity in a given year. (Compustat)
ROA	Return on assets, measured by net income before extraordinary items divided by total assets. (Compustat)
Leverage	Debt in current liabilities plus long-term debt, scaled by total assets. (Compustat)
EarnVolatility	Natural logarithm of standard deviation of a firm's earnings from a time-series rolling window over past five years with at least three years of data. (I/B/E/S summary)
EarnLoss	An indicator variable equal to one if a firm reports negative earnings in a year, and zero otherwise. (I/B/E/S summary)
CarbonEmission	Natural logarithm of total Scope 1, 2, and 3 carbon emissions. (Refinitiv ESG)
FHorizon	Forecasting horizon, measured by the median number of days between analyst forecast dates and earnings announcement date in a given year. (I/B/E/S detail)

FinancialOpaqueness	A measure of firm-level financial transparency measured by country-, industry-, and year-adjusted total scaled accruals. Scaled accruals are calculated as the absolute value of a firm's scaled accruals averaged over the past three years of each firm. FinancialOpaqueness is a dummy variable, which equals one if a firm has a higher than the country-industry-year mean of scaled accruals, and otherwise zero. (see page 733, Dhaliwal et al., 2012) (Compustat)
ADR	An indicate variable equal to one if a non-US company is listed in the US market via American Depositary Receipts. (CRSP)
#Analysts	Natural logarithm of the number of sell-side analysts following the firm in a given year. (I/B/E/S summary)
<i>Other Variables</i>	
TCFD Supporter	An indicator variable equal to one if the firm is a TCFD supporter, and zero otherwise. (TCFD website: https://www.fsb-tcfd.org/support-tcfd/)
EIncidents	Natural logarithm of one plus the number of environment-related adverse incidents. (RepRisk)
Capx	Capital expenditure, scaled by total assets. (Compustat)
PPE	Property, plant and equipment, scaled by total assets. (Compustat)
EmissionIntensity	Natural logarithm of total carbon emissions divided by a firm's revenue in US dollars. (LSEG ESG)
Dividend	An indicator variable which equals one if the firm has common dividend payment, and zero otherwise. (Compustat & CRSP)
#Firms	Natural logarithm of the number of firms covered by a sell-side financial analyst at the end of year. (I/B/E/S detail)
BrokerSize	Natural logarithm of the number of analysts in the brokerage company in a given year at the end of year. (I/B/E/S detail)

References

- Addoum, J. M., Ng, D. T. & Ortiz-Bobea, A. 2020. Temperature shocks and establishment sales. *The Review of Financial Studies*, 33, 1331-1366.
- Addoum, J. M., Ng, D. T. & Ortiz-Bobea, A. 2023. Temperature shocks and industry earnings news. *Journal of Financial Economics*, 150, 1-45.
- Aerts, W., Cormier, D. & Magnan, M. 2008. Corporate environmental disclosure, financial markets and the media: An international perspective. *Ecological Economics*, 64, 643-659.
- Ahn, B. H., Patatoukas, P. N. & Skiadopoulos, G. S. 2024. Material ESG Alpha: A Fundamentals-Based Perspective. *The Accounting Review*, 99, 1-27.
- Al-Tuwaijri, S. A., Christensen, T. E. & Hughes Li, K. 2004. The relations among environmental disclosure, environmental performance, and economic performance: a simultaneous equations approach. *Accounting, Organizations and Society*, 29, 447-471.
- Albuquerque, R., Koskinen, Y. & Zhang, C. 2019. Corporate social responsibility and firm risk: Theory and empirical evidence. *Management Science*, 65, 4451-4469.
- Baldauf, M., Garlappi, L. & Yannelis, C. 2020. Does climate change affect real estate prices? Only if you believe in it. *The Review of Financial Studies*, 33, 1256-1295.
- Balvers, R., Du, D. & Zhao, X. 2017. Temperature shocks and the cost of equity capital: Implications for climate change perceptions. *Journal of Banking & Finance*, 77, 18-34.
- Becchetti, L., Ciciretti, R. & Giovannelli, A. 2013. Corporate social responsibility and earnings forecasting unbiasedness. *Journal of Banking & Finance*, 37, 3654-3668.
- Ben-Amar, W., Herrera, D. C. & Martinez, I. 2024. Do climate risk disclosures matter to financial analysts? *Journal of Business Finance & Accounting*, 51, 2153-2180.
- Beyer, A., Cohen, D. A., Lys, T. Z. & Walther, B. R. 2010. The financial reporting environment: Review of the recent literature. *Journal of Accounting and Economics*, 50, 296-343.
- Bhat, G., Hope, O. K. & Kang, T. 2006. Does corporate governance transparency affect the accuracy of analyst forecasts? *Accounting & Finance*, 46, 715-732.
- Bhushan, R. 1989. Firm characteristics and analyst following. *Journal of Accounting and Economics*, 11, 255-274.
- Bingler, J. A., Kraus, M., Leippold, M. & Webersinke, N. 2022. Cheap talk and cherry-picking: What climatebert has to say on corporate climate risk disclosures. *Finance Research Letters*, 102776.
- Bolton, P. & Kacperczyk, M. T. 2021. Carbon Disclosure and the Cost of Capital. *Available at SSRN 3755613*.
- Bolton, P. & Kacperczyk, M. T. 2023. Global pricing of carbon-transition risk. *The Journal of Finance*, 78, 3677-3754.
- Buehlmaier, M. M. & Whited, T. M. 2018. Are financial constraints priced? Evidence from textual analysis. *The Review of Financial Studies*, 31, 2693-2728.
- Call, A. C., Hewitt, M., Watkins, J. & Yohn, T. L. 2021. Analysts' annual earnings forecasts and changes to the I/B/E/S database. *Review of Accounting Studies*, 26, 1-36.
- Campbell, J. L., Chen, H., Dhaliwal, D. S., Lu, H.-m. & Steele, L. B. 2014. The information content of mandatory risk factor disclosures in corporate filings. *Review of Accounting Studies*, 19, 396-455.
- Cannon, J. N., Ling, Z., Wang, Q. & Watanabe, O. V. 2020. 10-K Disclosure of Corporate Social Responsibility and Firms' Competitive Advantages. *European Accounting Review*, 29, 85-113.
- Chen, S., Miao, B. & Shevlin, T. 2015. A new measure of disclosure quality: The level of disaggregation of accounting data in annual reports. *Journal of Accounting Research*, 53, 1017-1054.

- Chen, T., Xie, L. & Zhang, Y. 2017. How does analysts' forecast quality relate to corporate investment efficiency? *Journal of Corporate Finance*, 43, 217-240.
- Christensen, H. B., Hail, L. & Leuz, C. 2021. Mandatory CSR and sustainability reporting: Economic analysis and literature review. *Review of Accounting Studies*, 26, 1176-1248.
- Clarkson, P. M., Li, Y., Pinnuck, M. & Richardson, G. D. 2015. The valuation relevance of greenhouse gas emissions under the European Union carbon emissions trading scheme. *European Accounting Review*, 24, 551-580.
- Clarkson, P. M., Li, Y., Richardson, G. D. & Vasvari, F. P. 2008. Revisiting the relation between environmental performance and environmental disclosure: An empirical analysis. *Accounting, Organizations and Society*, 33, 303-327.
- Cohen, L., Gurun, U. G. & Nguyen, Q. H. 2020. The ESG-innovation disconnect: Evidence from green patenting. National Bureau of Economic Research.
- Cormier, D., Magnan, M. & Van Velthoven, B. 2005. Environmental disclosure quality in large German companies: economic incentives, public pressures or institutional conditions? *European Accounting Review*, 14, 3-39.
- Cukuliza, C., Kumar, A., Xin, W. & Zhang, C. 2021. Climate Change, Analyst Forecasts, and Market Behavior. *Analyst Forecasts, and Market Behavior (February 18, 2021)*.
- Cui, J., Jo, H. & Na, H. 2018. Does corporate social responsibility affect information asymmetry? *Journal of Business Ethics*, 148, 549-572.
- Dal Maso, L. & Rees, B. 2016. Nonfinancial Disclosure and Analyst Forecast Accuracy: Evidences from CO2 Emission and Corporate Social Responsibility Disclosures in the US. Available at SSRN 2795268.
- Das, S., Levine, C. B. & Sivaramakrishnan, K. 1998. Earnings predictability and bias in analysts' earnings forecasts. *The Accounting Review*, 277-294.
- Derrien, F., Krueger, P., Landier, A. & Yao, T. 2021. ESG news, future cash flows, and firm value. *Swiss Finance Institute Research Paper*.
- Dhaliwal, D. S., Li, O. Z., Tsang, A. & Yang, Y. G. 2011. Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting. *The Accounting Review*, 86, 59-100.
- Dhaliwal, D. S., Radhakrishnan, S., Tsang, A. & Yang, Y. G. 2012. Nonfinancial disclosure and analyst forecast accuracy: International evidence on corporate social responsibility disclosure. *The Accounting Review*, 87, 723-759.
- Dong, R., Fisman, R., Wang, Y. & Xu, N. 2021. Air pollution, affect, and forecasting bias: Evidence from Chinese financial analysts. *Journal of Financial Economics*, 139, 971-984.
- Eccles, R. G., Serafeim, G. & Krzus, M. P. 2011. Market interest in nonfinancial information. *Journal of Applied Corporate Finance*, 23, 113-127.
- Eis, J., Schafer, J., Carr, B., Clawson, F., Borduas, T., Léveillé, M., Millot, B., Chew, E., Isleib, F. & Borovac, E. 2019. Changing Course: A comprehensive investor guide to scenario-based methods for climate risk assessment, in response to the TCFD. *UNEP Finance Initiative*.
- El Ghoul, S., Guedhami, O., Wei, Z. & Zhu, Y. 2023. Does public corruption affect analyst forecast quality? *Journal of Banking & Finance*, 154, 106860.
- Engle, R. F., Giglio, S., Kelly, B., Lee, H. & Stroebe, J. 2020. Hedging climate change news. *The Review of Financial Studies*, 33, 1184-1216.
- Fiechter, P., Hitz, J. M. & Lehmann, N. 2022. Real effects of a widespread CSR reporting mandate: Evidence from the European Union's CSR Directive. *Journal of Accounting Research*, 60, 1499-1549.
- Financial Times. 2024. Time for investors to turn up the heat on climate governance. Retrieved from: <https://www.ft.com/content/a693d934-e940-41d8-ab40-2bdde1bc6ccf>.

- Fisher, A. C., Hanemann, W. M., Roberts, M. J. & Schlenker, W. 2012. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather: comment. *American Economic Review*, 102, 3749-60.
- Flammer, C. 2021. Corporate green bonds. *Journal of Financial Economics*, 142, 499-516.
- Flammer, C., Hong, B. & Minor, D. 2019. Corporate governance and the rise of integrating corporate social responsibility criteria in executive compensation: Effectiveness and implications for firm outcomes. *Strategic Management Journal*, 40, 1097-1122.
- Flores, E., Fasan, M., Mendes-da-Silva, W. & Sampaio, J. O. 2019. Integrated reporting and capital markets in an international setting: The role of financial analysts. *Business Strategy and the Environment*, 28, 1465-1480.
- Gentzkow, M., Kelly, B. & Taddy, M. 2019. Text as data. *Journal of Economic Literature*, 57, 535-74.
- Gibbons, B. 2024. The Financially Material Effects of Mandatory Nonfinancial Disclosure. *Journal of Accounting Research*, 62, 1711-1754.
- Giglio, S., Kelly, B. & Stroebe, J. 2021a. Climate finance. *Annual Review of Financial Economics*, 13, 15-36.
- Giglio, S., Maggiori, M., Rao, K., Stroebe, J. & Weber, A. 2021b. Climate change and long-run discount rates: Evidence from real estate. *The Review of Financial Studies*, 34, 3527-3571.
- Graff Zivin, J. & Neidell, M. 2014. Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, 32, 1-26.
- Griffin, P. A., Lont, D. H. & Sun, E. Y. 2017. The relevance to investors of greenhouse gas emission disclosures. *Contemporary Accounting Research*, 34, 1265-1297.
- Hahn, R., Reimsbach, D. & Schiemann, F. 2015. Organizations, climate change, and transparency: Reviewing the literature on carbon disclosure. *Organization & Environment*, 28, 80-102.
- Hail, L., Leuz, C. & Wysocki, P. 2010. Global accounting convergence and the potential adoption of IFRS by the US (Part II): Political factors and future scenarios for US accounting standards. *Accounting Horizons*, 24, 567-588.
- Han, Y., Mao, C. X., Tan, H. & Zhang, C. 2020. Distracted Analysts: Evidence from Climatic Disasters. *Fox School of Business Research Paper Forthcoming*.
- Hansen, S., McMahon, M. & Prat, A. 2017. Transparency and deliberation within the FOMC: a computational linguistics approach. *The Quarterly Journal of Economics*, 133, 801-870.
- Hirshleifer, D., Lourie, B., Ruchti, T. G. & Truong, P. 2021. First impression bias: Evidence from analyst forecasts. *Review of Finance*, 25, 325-364.
- Hong, H., Li, F. W. & Xu, J. 2019. Climate risks and market efficiency. *Journal of Econometrics*, 208, 265-281.
- Hope, O. K. 2003. Disclosure practices, enforcement of accounting standards, and analysts' forecast accuracy: An international study. *Journal of Accounting Research*, 41, 235-272.
- Hugon, A. & Law, K. 2019. Impact of climate change on firm earnings: evidence from temperature anomalies. *Available at SSRN 3271386*.
- Ilhan, E., Krueger, P., Sautner, Z. & Starks, L. T. 2023. Climate risk disclosure and institutional investors. *The Review of Financial Studies*, 36, 2617-2650.
- Ioannou, I., Li, S. X. & Serafeim, G. 2016. The effect of target difficulty on target completion: The case of reducing carbon emissions. *The Accounting Review*, 91, 1467-1492.
- Jackson, A. R. 2005. Trade generation, reputation, and sell-side analysts. *The Journal of Finance*, 60, 673-717.
- Kennard, A. 2020. The enemy of my enemy: When firms support climate change regulation. *International Organization*, 74, 187-221.
- Khan, M., Serafeim, G. & Yoon, A. 2016. Corporate sustainability: First evidence on materiality. *The Accounting Review*, 91, 1697-1724.

- Kim, J.-B., Wang, C. & Wu, F. 2023. The real effects of risk disclosures: evidence from climate change reporting in 10-Ks. *Review of Accounting Studies*, 28, 2271-2318.
- Kravet, T. & Muslu, V. 2013. Textual risk disclosures and investors' risk perceptions. *Review of Accounting Studies*, 18, 1088-1122.
- Krueger, P., Sautner, Z. & Starks, L. T. 2020. The importance of climate risks for institutional investors. *The Review of Financial Studies*, 33, 1067-1111.
- Lang, M. H. & Lundholm, R. J. 1996. Corporate disclosure policy and analyst behavior. *The Accounting Review*, 467-492.
- Law, K. 2023. Good-Bye IBES (or Not?). *Journal of Financial Reporting*, 8, 41-61.
- Lehavy, R., Li, F. & Merkley, K. 2011. The effect of annual report readability on analyst following and the properties of their earnings forecasts. *The Accounting Review*, 86, 1087-1115.
- Leuz, C. & Verrecchia, R. E. 2000. The Economic Consequences of Increased Disclosure. *Journal of Accounting Research*, 38.
- Leuz, C. & Wysocki, P. D. 2016. The economics of disclosure and financial reporting regulation: Evidence and suggestions for future research. *Journal of Accounting Research*, 54, 525-622.
- Lim, T. 2001. Rationality and analysts' forecast bias. *The Journal of Finance*, 56, 369-385.
- Loughran, T. & McDonald, B. 2014. Measuring readability in financial disclosures. *The Journal of Finance*, 69, 1643-1671.
- Loughran, T. & McDonald, B. 2016. Textual analysis in accounting and finance: A survey. *Journal of Accounting Research*, 54, 1187-1230.
- Lundholm, R. & Myers, L. A. 2002. Bringing the future forward: the effect of disclosure on the returns-earnings relation. *Journal of Accounting Research*, 40, 809-839.
- Matsumura, E. M., Prakash, R. & Vera-Muñoz, S. C. 2013. Firm-value effects of carbon emissions and carbon disclosures. *The Accounting Review*, 89, 695-724.
- Matsumura, E. M., Prakash, R. & Vera-Muñoz, S. C. 2024. Climate-risk materiality and firm risk. *Review of Accounting Studies*, 29, 33-74.
- McGrath, J. 2019. S&P issues warning on ESG credit analysis. <https://esgclarity.com/sp-issues-warning-on-esg-credit-analysis/>.
- Merkley, K. J. 2013. Narrative disclosure and earnings performance: Evidence from R&D disclosures. *The Accounting Review*, 89, 725-757.
- Michaely, R., Rubin, A., Segal, D. & Vadrashko, A. 2024. Do differences in analyst quality matter for investors relying on consensus information? *Management Science*, 70, 751-772.
- Michelon, G. & Parbonetti, A. 2012. The effect of corporate governance on sustainability disclosure. *Journal of Management & Governance*, 16, 477-509.
- Muslu, V., Mutlu, S., Radhakrishnan, S. & Tsang, A. 2019. Corporate social responsibility report narratives and analyst forecast accuracy. *Journal of Business Ethics*, 154, 1119-1142.
- Nagar, V. & Schoenfeld, J. 2024. Measuring weather exposure with annual reports. *Review of Accounting Studies*, 29, 1-32.
- Oliver, C. 1991. Strategic responses to institutional processes. *Academy of Management Review*, 16, 145-179.
- Painter, M. 2020. An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics*, 135, 468-482.
- Pankratz, N., Bauer, R. & Derwall, J. 2023. Climate change, firm performance, and investor surprises. *Management Science*, 69, 7352-7398.
- Payne, J. L. & Thomas, W. B. 2003. The implications of using stock-split adjusted I/B/E/S data in empirical research. *The Accounting Review*, 78, 1049-1067.
- Qian, W. & Schaltegger, S. 2017. Revisiting carbon disclosure and performance: Legitimacy and management views. *The British Accounting Review*, 49, 365-379.

- Ramelli, S., Ossola, E. & Rancan, M. 2021. Stock price effects of climate activism: Evidence from the first global climate strike. *Journal of Corporate Finance*, 69, 102018.
- Sautner, Z., Van Lent, L., Vilkov, G. & Zhang, R. 2023. Firm-level climate change exposure. *The Journal of Finance*, 78, 1449-1498.
- Schwab, K. 2019. The Global Competitiveness Report 2019. Retrieved from: <https://www.weforum.org/publications/how-to-end-a-decade-of-lost-productivity-growth/>. World Economic Forum.
- Sharfman, M. P. & Fernando, C. S. 2008. Environmental risk management and the cost of capital. *Strategic Management Journal*, 29, 569-592.
- Starks, L. T. 2023. Presidential address: Sustainable finance and ESG issues—Value versus values. *The Journal of Finance*, 78, 1837-1872.
- TCFD 2017. Implementing the recommendations of The Task Force on Climate-Related Financial Disclosures.
- TCFD 2019. Task Force on Climate-related Financial Disclosures: Status Report.
- TCFD 2022. Task Force on Climate-related Financial Disclosures: Status Report.
- Te Liew, W., Adhitya, A. & Srinivasan, R. 2014. Sustainability trends in the process industries: A text mining-based analysis. *Computers in Industry*, 65, 393-400.
- Velte, P. & Stawinoga, M. 2020. Do chief sustainability officers and CSR committees influence CSR-related outcomes? A structured literature review based on empirical-quantitative research findings. *Journal of Management Control*, 31, 333-377.
- Weinhofer, G. & Busch, T. 2013. Corporate strategies for managing climate risks. *Business Strategy and the Environment*, 22, 121-144.

Appendix

Section I. Firm-level Climate Change Disclosure Score Calculation

This section provides detailed description of how our main climate disclosure measure is estimated using the bag-of-words model in three steps: (1) developing a climate change vocabulary (CCV); (2) forming a climate change corpus; and (3) calculating a correlation between a fixed climate change vocabulary and a firm's climate narratives in its annual reports.

Step 1: Developing a fixed climate change vocabulary

We first identify a training sample that can effectively capture the common terms used if a firm follows the TCFD reporting framework to make its climate change disclosure. With this purpose in mind, we download a list of firms from the five sample countries that are supporters of the TCFD reporting recommendations. Specifically, there are 24 listed firms in Australia, 13 in Canada, 16 in France, 28 in the UK, and 24 in the US. Since the TCFD company supporters only account for a small portion of firms in each country, our hypothesis testing mainly relies on an out-of-sample performance and is therefore less likely to be confounded by the overfitting concern (Buehlmaier and Whited, 2018).

Next, we retrieve annual reports and voluntary sustainability reports, if available, for the list of TCFD company supporters to form a base for our training sample (Buehlmaier and Whited, 2018; Cannon et al., 2020; Engle et al., 2020). We impose two search criteria for these company reports: (1) the reports must be filed from 2017 to 2019 because this was the initial year when TCFD recommendations were published; and (2) the reports contain a specific section of climate change disclosure in accordance with the TCFD recommendations. In this way, we collected a total of 162 reports that contain textual TCFD-aligned climate change information, including 38 reports from Australia, 21 reports from Canada, 22 reports from France, 48 reports from the UK, and 33 reports from the US. We manually extract *the TCFD-aligned climate change disclosure section* from these textual documents and follow Merkley (2013) and Engle et al. (2020) to create a climate change vocabulary for each country as follows.

First, the extracted climate disclosure texts are structurally processed by removing punctuation and stop words, stripping white space, and stemming words (Gentzkow et al., 2019). In the stemming process, words are converted into their root or basic stem to ensure uniform feature forms and reduce feature dimensions. Second, the TCFD-aligned climate disclosure in each company report has four subsections, namely, governance, strategy, risk

management, and metrics/targets. This reporting requirement allows us to form training samples for each reporting category quite reliably. Third, we tokenize the processed climate change texts in each of the four subsections by words with n length, referred to as n -grams. The n -gram words are aggregated across the firms in each country to form a numerical vector. These words and their frequencies are defined as a category-specific climate change vocabulary for a given country. Finally, we aggregate the four category-level vocabularies to establish an overall climate change vocabulary.

Step 2: Extracting climate-related keywords from firm annual reports

To begin, we convert firms' annual reports in the final sample into processed text documents by removing punctuation and stop words, stripping white space, and stemming words. Firms' annual reports contain rich information about their financial and nonfinancial fundamentals. To enhance the relevance of our climate-related disclosure calibration, we first identify a series of keywords clearly related to climate change. These keywords are 'climate change', 'climate risk', 'climate opportunity', 'carbon emission', 'GHG emission', and 'greenhouse gas'. If a firm's annual report does not contain any of these terms, we assume the firm does not disclose any climate narratives in its annual report. For firms with annual reports that contain any of these keywords, we only retain the pages where any of these keywords were mentioned as its climate change corpus for our subsequent analysis of the firm's climate change disclosure intensity.

Step 3: Comparing climate-related texts with the climate change vocabulary

With the climate change vocabulary and climate change-related text documents extracted from firms' annual reports, we are able to compute the similarity between each firm's narrative disclosure in its annual report potentially relevant to climate change and the fixed vocabulary and discern how informative a firm's annual report is about its climate change exposure. An effective and practical measure for text informativeness is term frequency-inverse document frequency (tf_idf). The tf_idf is a product of term frequency (tf) and inverse document frequency (idf). Below is the term frequency matrix for climate change vocabulary and a firm's annual report.

		CCV's frequency	Firm i's frequency
N-dimensional Vector	Term ₁	$f_{t_1,CCV}$	$f_{t_1,1,t} \quad f_{t_1,2,t} \quad \cdots \quad f_{t_1,i,t}$
	Term ₂	$f_{t_2,CCV}$	$f_{t_2,1,t} \quad f_{t_2,2,t} \quad \cdots \quad f_{t_2,i,t}$
	Term ₃	$f_{t_3,CCV}$	$f_{t_3,1,t} \quad f_{t_3,2,t} \quad \cdots \quad f_{t_3,i,t}$
	\vdots	\vdots	\ddots
	Term _n	$f_{t_n,CCV}$	$f_{t_n,1,t} \quad f_{t_n,2,t} \quad \cdots \quad f_{t_n,i,t}$

D

The text informativeness measure tf_idf is estimated as:

$$tf_idf = tf * idf = f_{t,d} * \log\left(\frac{D}{d_t}\right)$$

$f_{t,d}$ represents the term frequency of term t in document d , D is the total number of documents in the corpus, and d_t is the number of documents containing term t . This method penalizes highly frequent words because of low idf as well as rare words because of low tf (Gentzkow et al., 2019; Hansen et al., 2017; Te Liew et al., 2014). The tf_idf is calculated for each term in the climate change vocabulary to evaluate how important and informative these terms are in the whole sample.

Each climate-related n-gram term w_n in a firm's annual report i has a $tf_idf_{t_n,i,t}$ value and a firm has a N-dimensional vector of $tf_idf_{t_n,i,j}$ in year j . The firm i 's vector has the same length as the vector of climate change vocabulary document, $tf_idf_{t_n,CCV}$ when the same climate-related words in both the vocabulary and annual reports are matched. Hence, the whole climate change corpus in our study has the matrix as below:

		CCV's vector	Firm i's vector
N-dimensional Vector	Term ₁	$tf_idf_{t_1,CCV}$	$tf_idf_{t_1,1,j} \quad tf_idf_{t_1,2,j} \quad \cdots \quad tf_idf_{t_1,i,j}$
	Term ₂	$tf_idf_{t_2,CCV}$	$tf_idf_{t_2,1,j} \quad tf_idf_{t_2,2,j} \quad \cdots \quad tf_idf_{t_2,i,j}$
	Term ₃	$tf_idf_{t_3,CCV}$	$tf_idf_{t_3,1,j} \quad tf_idf_{t_3,2,j} \quad \cdots \quad tf_idf_{t_3,i,j}$
	\vdots	\vdots	\ddots
	Term _n	$tf_idf_{t_n,CCV}$	$tf_idf_{t_n,1,j} \quad tf_idf_{t_n,2,j} \quad \cdots \quad tf_idf_{t_n,i,j}$

The climate change similarity score, denoted as *CCSS*, is estimated as the cosine similarity shown below:

$$CCSS_{i,j} = \cosine(tf_idf_{t_{n,i,j}}, tf_idf_{t_{n,ccv}}) = \frac{tf_idf_{t_{n,i,j}} \cdot tf_idf_{t_{n,ccv}}}{|tf_idf_{t_{n,i,j}}| |tf_idf_{t_{n,ccv}}|}$$

$$= \frac{\sum_{n=1}^N (tf_idf_{t_{n,i,j}} * tf_idf_{t_{n,ccv}})}{\sqrt{(\sum_{n=1}^N tf_idf_{t_{n,i,j}})^2} \sqrt{(\sum_{n=1}^N tf_idf_{t_{n,ccv}})^2}}$$

We designate this climate change disclosure measure as the Climate Change Similarity Score (*CCSS*). We further construct category-level climate change vocabularies to calculate category-level disclosure scores in the same manner as *CCSS*, namely *GO*, *ST*, *RM*, and *MT*, which represent category-level climate change disclosure measures for governance, strategy, risk management, and metrics and targets, respectively.

Section II. Validation Tests of Firm-level Climate Change Disclosures

One may argue that our sample spans from 2010 to 2019, which means that some *CCSS* values were estimated prior to the launch of TCFD in 2017. This may induce a potential look-ahead bias in our key disclosure measurement. However, we believe that this concern is less likely to affect our hypothesis testing because our research focuses on the extent of climate-related financial disclosures rather than compliance with TCFD reporting requirements. However, as a way of verification, we show in Table IA. II that our *CCSS* measure is positively correlated with firm-level carbon emissions on the full sample in columns (1)-(2) as well as a sample with nonzero *CCSS* estimates after controlling for other firm-level characteristics in columns (3)-(4), suggesting that firms with high climate risk exposures are more likely to disclose climate information in their financial reports. The association persists in the subperiods before and after the launch of TCFD recommendations in 2017 (see columns (5)-(6), confirming the climate information content of our *CCSS* measurement even before the release of TCFD reporting framework.

[Insert Table IA. II about here]

Second, our hypothesis testing relies on the alignment of our climate disclosure measure with TCFD reporting framework which should capture financially material climate information disclosure. To demonstrate the alignment between *CCSS* and TCFD reporting framework, we show in Table IA. III that the *CCSS* score tends to be higher among firms that support TCFD reporting after the release of the reporting framework. We further decompose *CCSS* into four

TCFD-defined climate information categories including Governance, Strategy, Risk Management and Metrics & Targets, and show the dynamics of these disclosure subcategories over time in Figure IA.I. While these sub categorical disclosure scores increase slightly after the Paris Agreement, these scores increase even more sharply after the launch of the TCFD recommendations. In particular, the Governance (*GO*) and Risk Management (*RM*) scores exhibited the largest increases by 15.08% and 11.49%, respectively, from their pre-TCFD level after the publication of TCFD recommendations. The overall evidence corroborates the alignment between our climate measure and TCFD reporting recommendations.

[Insert Table IA. III about here]

To further strengthen the validation test for our main estimates, we inspect the changes in *CCSS* around two exogenous policy shocks that are expected to elevate the intensity of financially material climate information disclosure by firms. First, in 2015, France passed *Article 173*, as a part of the *Energy Transition Act*, mandating climate change disclosure for listed firms (*Article 173-VI*) and institutional investors (*Article 173-IV*). This new regulation was expected to enhance firm-level climate disclosure directly through mandated reporting requirements and indirectly through an elevated demand for climate change information from their investors (Ilhan et al., 2023). In support of the validity of our *CCSS* measure, we anticipate a significant increase in *CCSS* for companies held by French institutional investors following the passage of the regulation in August 2015. To exercise this validation test, we obtain the institutional ownership data from the Factset Ownership database and merge it with our primary sample. We introduce a variable, *IOFrance*, representing the firm's equity ownership held by French institutional investors, and a dummy variable, *PostArticle 173,t*, which is equal to one for the year 2015 and beyond, and zero otherwise. We then estimate the following DiD regression using the sample between 2010 and 2019:

$$CCSS_{i,t} = \alpha + \beta_1 IOFrance_{i,t} \times Post_{Article\ 173,t} + \beta_2 IOFrance_{i,t} + \gamma FVEC_{i,t} + Fixed\ effects + \varepsilon_{i,t} \quad (1)$$

Following Fiechter et al. (2022) and Ilhan et al. (2023), we include firm size measured by the natural logarithm of total assets (*Size*), market-to-book ratio (*MTB*), return on assets (*ROA*), leverage ratio (*Leverage*), property, plant and equipment scaled by total assets (*PPE*), capital expenditure scaled by total assets (*Capx*) as control variables. Firm-level carbon emissions amount (*CarbonEmission*) is also added as a strong predictor of climate change disclosures according to prior studies (Al-Tuwaijri et al., 2004; Clarkson et al., 2008; Qian and Schaltegger,

2017). We saturate the model with firm and industry-year fixed effects to account for possible unobservable heterogeneities in firm characteristics as well as industry-year specific trends in climate change disclosures.

Another policy shock to firm-level climate disclosure we consider is the Non-Financial Reporting Directive passed in 2014 in the EU region (EU NFR Directive). This regulation mandates large listed firms in EU to include non-financial statements regarding environmental matters, social responsibility, employee treatment and anti-corruption in their annual reports (Fiechter et al., 2022). This legislation would presumably lead to a higher level of climate change disclosure in firms from France and the UK, compared to those from the other three countries in our sample. Following this logic, we examine the sensitivity of CCSS scores to the EU NFR Directive. Following Fiechter et al. (2022), we consider firms in France and the UK with more than 500 employees and total assets exceeding EUR 20 million (or EUR 40 million in revenue) as the treatment group, and other firms in Australia, Canada, and the US as the control group. Given that the NFR Directive applies to large and listed firms (Fiechter et al., 2022), we use the propensity score matching approach to find a more comparable control sample for our treatment firms. Specifically, we form the final control sample by matching treatment firms with firms in the initial control sample in the benchmark year, 2013, using the one-to-one nearest neighbour matching method with replacement based on observable firm characteristics (i.e., control variables specified in Equation (1) above). Like the first policy shock, we estimate the disclosure effect of the second policy shock using the following DiD regression framework from 2010 to 2019:

$$CCSS_{i,t} = \alpha + \beta_1 Treat_i \times Post_{EU\ NFR,t} + \gamma' FVEC_{i,t} + Fixed\ effects + \varepsilon_{i,t} \quad (2)$$

$Treat_i$ is an indicator variable which takes a value of one for treated firms (firms from France and the UK) and a value of zero for control firms. $Post_{EU\ NFR,t}$ is equal to one for observations following the passage of the EU NFR Directive in 2014 and zero otherwise. The vector of control variables ($FVEC$) is the same as those specified in Equation (2).

Table IA. IV reports the DiD regression results of firm-level climate change disclosures around two climate policies. Column (1) shows a consistently positive and significant coefficient on $IOFrance \times Post$, suggesting that firms with a high level of French institutional ownership effectively responded to the passage of Article 173 and provided more climate change disclosure as reflected by a significantly higher value of CCSS. This result also holds

for a sample of firms with positive *CCSS* scores in column (2). Turning to EU NFR Directive, column (3) shows the significantly positive coefficient estimate of $Treat \times Post$ in the matched sample with and without replacement, suggesting that treated firms' climate narratives in its annual report, measured by our climate disclosure score, *CCSS*, increased significantly following the EU NFR Directive, relative to the control firms from non-EU countries.

[Insert Table IA. IV about here]

To assess the identifying assumption for the DiD estimator, we chart the dynamic effects of Article 173 over a four-year horizon before and after its passage in Panel A of Figure IA. II. It is important to note that there are generally no significant differences of *CCSS* scores between firms held by French investors and those not held by French investors prior to the regulatory change, but a sharp increase of *CCSS* scores for firms held by French investors after the regulatory reform, substantiating the validity of the DiD estimator.

We also check the identifying assumption of the exogenous shock induced by the EU NFR Directive by plotting out the dynamic treatment effects surrounding the passage of the policy over a nine-year window (from four years before to four years after the shock) in Panel B of Figure IA. II. Substantiating the validity of this identification strategy, we observe insignificant differences in *CCSS* between treated and control firms prior to the passage of the Directive, but a sharp increase in *CCSS* among treated firms from 2014 onwards. The overall results for a multitude of validation tests confirm the validity of our climate disclosure measure, *CCSS*, in capturing firm-level disclosure on its climate change information.

Figure IA. I: Climate Change Disclosure at the TCFD Subcategory Level

This figure presents the yearly sample average of each subcategory disclosure score throughout our sample period.

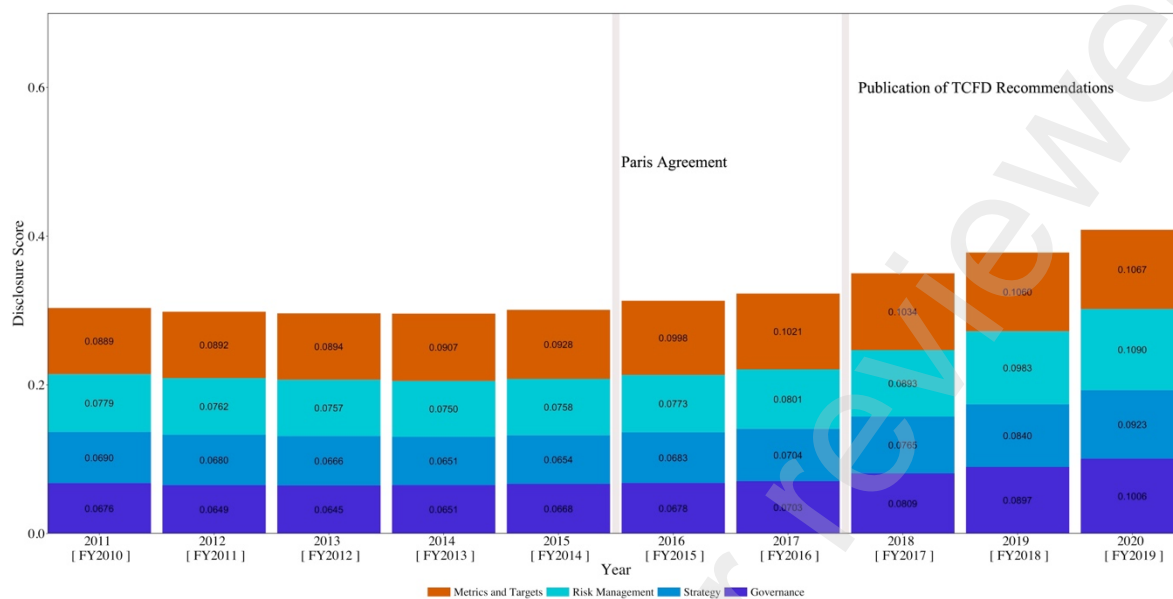
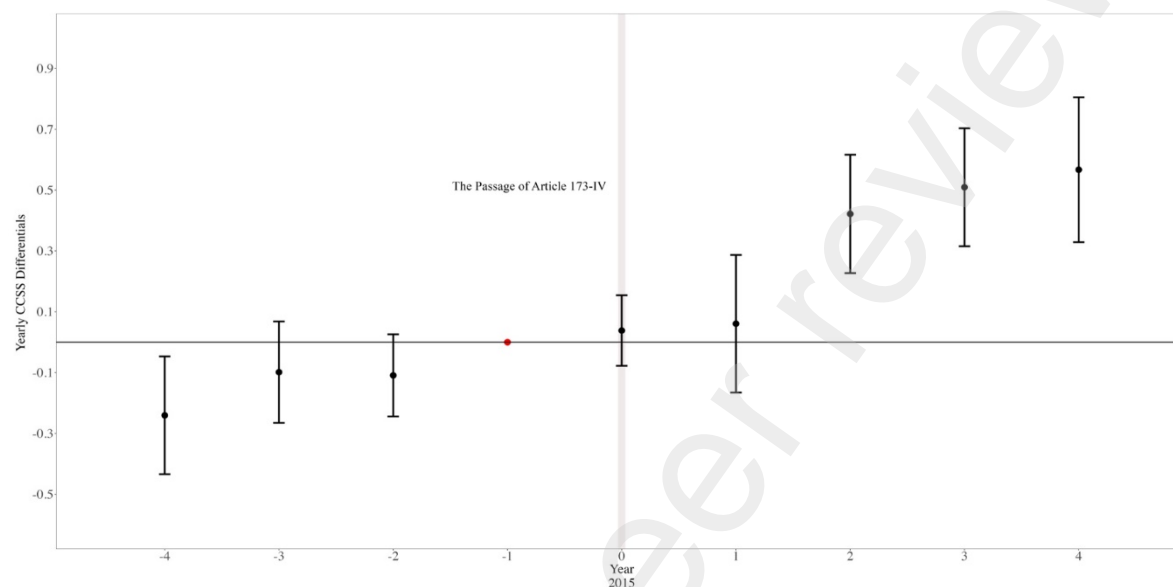


Figure IA. II: Dynamic Effects of Climate-related Disclosure Mandates

This figure plots the dynamic treatment effects of Article 173 and EU NFR Directive on firm-level climate change similarity scores in Panel A and B, respectively. Panel A displays the annual estimates of the average treatment effect, including 95% confidence intervals, in event-time relative to the passage of Article 173 in 2015 based on the regression results in column (1) of Table IA V, where year 2014 is the benchmark year (i.e., year = -1). Panel B presents the annual estimates of the average treatment effect, including 95% confidence intervals, in event-time relative to the passage of EU NFR Directive in 2014 based on the regression results in column (2) of Table IA V.

Panel A: Article 173



Panel B: EU NFR Directive

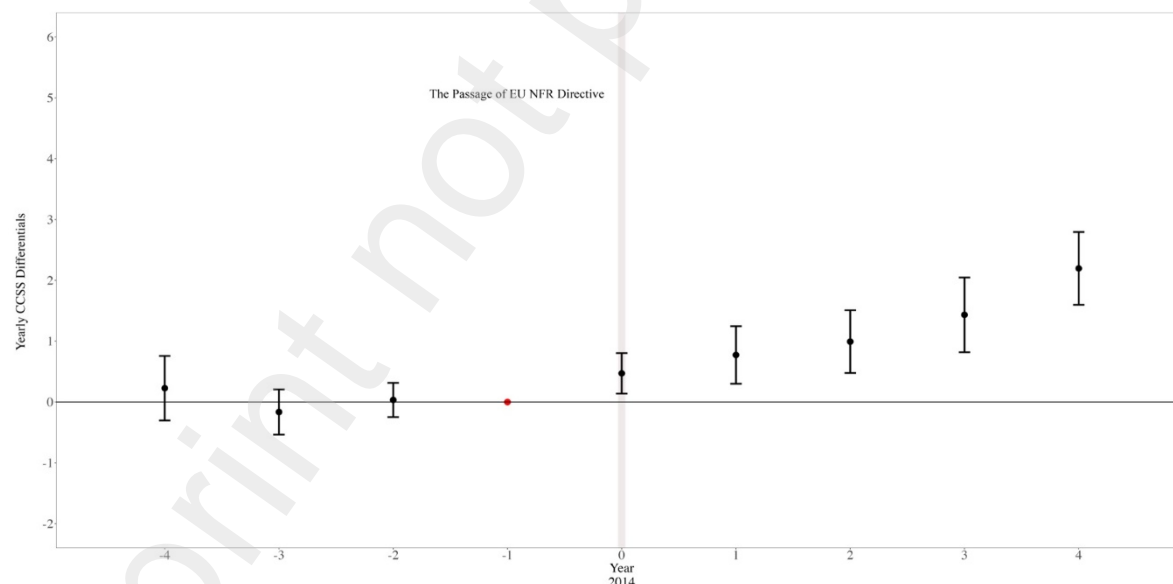


Table IA. I: Top-20 Keywords from climate change vocabulary for TCFD climate change disclosure subcategories by country

	Australia	Canada	France	UK	US
CCSS	climat chang, climat risk, long term, physic risk, scope emiss, transit risk, risk manag, risk opportun, climat relat, low carbon, climat relat risk, relat risk, emiss intens, scenario analysi, relat risk opportun, renew energi, carbon price, impact climat, ghg emiss, per cent	carbon price, climat chang, climat relat, climat relat risk, emiss intens, emiss reduct, energi effici, ghg emiss, product servic, relat risk, risk manag, risk opportun, weather event, carbon economi, long term, low carbon, relat risk opportun, scenario analysi, carbon intens, oil sand, lower carbon	board director, carbon footprint, carbon intens, climat chang, climat relat, energi effici, energi transit, gas emiss, ghg emiss, greenhous gas, greenhous gas emiss, long term, low carbon, physic risk, relat risk, renew energi, risk manag, risk opportun, transit risk, climat relat risk	carbon economi, climat chang, climat relat, climat relat risk, energi effici, ghg emiss, greenhous gas, long term, low carbon, relat risk, risk manag, risk opportun, transit risk, carbon intens, impact climat, physic risk, relat risk opportun, scope emiss, carbon emiss, climat risk, low carbon economi	carbon price, climat chang, climat relat, climat relat risk, climat risk, energi effici, extrem weather, ghg emiss, greenhous gas, long term, low carbon, physic risk, relat risk, renew energi, risk manag, risk opportun, scenario analysi, scope emiss, transit risk, weather event
Governance	climat chang, climat relat, risk opportun, relat risk, climat relat risk, risk manag, risk committe, relat risk opportun, includ climat, sustain committe, chang risk, climat chang risk, includ climat chang, board risk, manag climat, manag framework, group risk, risk manag framework, leadership team, audit risk, board risk committe, committe overse, manag climat relat	climat chang, climat relat, risk manag, risk opportun, climat relat risk, relat risk, board director, includ climat, relat issu, risk committe, committe board, relat risk opportun, climat relat issu, vice presid, corpor govern, govern committe, manag committe, chang risk, climat chang risk, committe overse, corpor govern committe, manag climat	board director, climat relat, execut committe, climat chang, sustain develop, busi unit, vice presid, chief execut, chief execut offic, execut offic, long term, manag committe, risk manag, relat issu, climat relat issu, risk opportun, social respons, supervisor board, group strategi, relat risk	climat chang, climat relat, risk opportun, relat risk, climat relat risk, risk manag, risk committe, climat risk, relat risk opportun, execut committe, chief execut, sustain committe, financi risk, chang risk, climat chang risk, committe group, group chief, risk climat, work group, includ climat, manag climat, risk climat chang	climat relat, relat risk, climat relat risk, climat chang, risk manag, risk opportun, environment social, board director, relat risk opportun, corpor govern, relat issu, board committe, risk committe, enterpris risk, includ climat, climat relat issu, corpor respons, manag committe, social respons, vice presid
Strategy	climat chang, long term, climat relat, scenario analysi, transit risk, risk opportun, low carbon, physic risk, impact climat, medium long, medium long term, relat risk, climat relat risk, renew energi, impact climat chang, extrem weather, physic impact, climat risk, carbon economi, energi effici	climat chang, climat relat, scenario analysi, low carbon, carbon price, relat risk, risk opportun, climat relat risk, oil sand, product servic, carbon intens, long term, ghg emiss, physic risk, extrem weather, weather event, green bond, transit risk, carbon economi, relat risk opportun	climat chang, climat relat, low carbon, transit risk, renew energi, physic risk, scenario analysi, risk opportun, relat risk, long term, green bond, energi transit, climat relat risk, real estat, suppli chain, energi effici, carbon intens, climat risk, greenhous gas, carbon price, posit impact, product servic	climat chang, low carbon, climat relat, physic risk, long term, carbon economi, transit risk, risk opportun, low carbon economi, relat risk, climat relat risk, extrem weather, energi effici, impact climat, transit low, transit low carbon, climat risk, scenario analysi, weather event, impact climat chang	climat chang, climat relat, scenario analysi, physic risk, carbon price, relat risk, climat relat risk, transit risk, renew energi, low carbon, risk opportun, extrem weather, weather event, energi effici, extrem weather event, climat risk, long term, product servic, climat scenario, sea level
Risk Management	climat chang, risk manag, climat relat, relat risk, climat relat risk, risk opportun, climat risk, manag framework, scenario analysi, carbon price, esg risk, risk manag framework, long term, risk assess, low carbon, manag risk, impact climat, climat resili, thermal coal, impact climat chang, relat risk opportun	climat chang, climat relat, risk manag, relat risk, climat relat risk, carbon price, ghg emiss, low carbon, risk opportun, carbon economi, chang risk, climat chang risk, product servic, weather event, carbon intens, low carbon economi, manag climat, identifi assess, lower carbon, climat risk, environment risk, impact climat, renew energi	climat chang, climat relat, risk manag, relat risk, transit risk, climat relat risk, physic risk, long term, human right, manag risk, low carbon, risk relat, impact climat, action plan, execut committe, risk identifi, risk map, suppli chain, air franc, axa franc, oper risk	climat chang, climat relat, risk manag, relat risk, climat relat risk, risk opportun, climat risk, princip risk, transit risk, physic risk, low carbon, long term, carbon economi, chang risk, relat risk opportun, climat chang risk, manag risk, scenario analysi, impact climat, manag process	climat chang, climat relat, risk manag, relat risk, climat relat risk, enterpris risk, risk opportun, energi effici, climat risk, enterpris risk manag, physic risk, long term, renew energi, risk assess, weather event, busi continu, manag team, product servic, sea level, extrem weather, manag process
Metrics and Targets	scope emiss, emiss intens, per cent, ghg emiss, scope scope, greenhous gas, gas emiss, greenhous gas emiss, emiss reduct, emiss scope, carbon emiss, climat chang, oper control, total scope, renew energi, reduct target, scope scope emiss, emiss reduct target, scope ghg, energi consumpt, scienc base	ghg emiss, low carbon, emiss intens, emiss reduct, climat relat, scope ghg, scope emiss, scope ghg emiss, million tonn, scope scope, oil sand, fort hill, oil equival, energi use, ghg intens, relat risk, absolut emiss, carbon intens, energi effici, carbon neutral, climat relat risk, energi consumpt, reduc ghg, renew energi	carbon footprint, greenhous gas, ghg emiss, gas emiss, greenhous gas emiss, emiss scope, carbon intens, energi consumpt, renew energi, energi effici, indirect emiss, scope emiss, low carbon, direct emiss, warm potenti, pari agreement, air franc, carbon emiss, climat relat, climat chang	scope emiss, greenhous gas, carbon intens, carbon emiss, market base, climat chang, ghg emiss, gas emiss, greenhous gas emiss, locat base, total scope, scope scope, scienc base, busi travel, low carbon, per cent, base emiss, emiss scope, carbon footprint, energi effici, energi use	ghg emiss, scope emiss, renew energi, greenhous gas, gas emiss, greenhous gas emiss, emiss reduct, climat chang, metric ton, scienc base, carbon emiss, scope scope, base target, scienc base target, energi consumpt, energi effici, climat relat, energi use, locat base, natur gas, scope ghg

Table IA. II: Climate Change Disclosure and Carbon Emissions

This table presents the regression results of climate change disclosure measure on firm-level carbon emissions. The dependent variable, $CCSS_{t+1}$, is the aggregate firm-level climate change disclosure variable at year $t+1$. $CarbonEmission_t$ is measured by the natural logarithm of total carbon emissions. $EmissionIntensity_t$ is calculated as the natural logarithm of total carbon emissions scaled by total revenue at year t . Control variables are firm size ($Size$), market-to-book ratio (MTB), return on assets (ROA), leverage ratio ($Leverage$), and capital expenditure ($Capx$). The t -statistics in parentheses are adjusted by standard errors clustered at the firm level. *, **, *** represent the 10%, 5% and 1% significance level, respectively.

	[1]	[2]	[3]	[4]	[5]	[6]
CarbonEmission _t	0.743*** (5.46)		0.740*** (5.28)		0.948*** (5.87)	0.588*** (3.94)
EmissionIntensity _t		0.556*** (5.55)		0.655*** (5.53)		
Size _t	1.188*** (10.73)	1.632*** (19.03)	0.960*** (8.21)	1.370*** (15.45)	1.064*** (8.10)	1.111*** (8.34)
MTB _t	0.035 (0.82)	0.059 (1.38)	0.0002 (0.00)	0.02 (0.38)	0.059 (1.21)	-0.007 (-0.13)
ROA _t	-0.126*** (-3.07)	-0.04 (-0.93)	-0.056 (-1.06)	-0.008 (-0.15)	-0.242*** (-4.50)	-0.009 (-0.15)
Leverage _t	-0.193*** (-3.25)	-0.198*** (-3.34)	-0.244*** (-3.27)	-0.262*** (-3.54)	-0.222*** (-3.20)	-0.107 (-1.37)
PPE _t	0.509*** (4.25)	0.523*** (4.43)	0.373*** (3.15)	0.363*** (3.12)	0.388** (2.51)	0.605*** (4.36)
Capx _t	-0.094 (-1.36)	-0.088 (-1.27)	-0.201*** (-2.62)	-0.198** (-2.56)	-0.103 (-1.02)	-0.065 (-0.76)
Sample	Full sample	Full sample	CCSS >0	CCSS >0	After 2017	Before 2017
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,214	17,214	9,512	9,512	7,320	9,894
Adjusted R2	0.56	0.56	0.47	0.47	0.64	0.52

Table IA. III: Climate Change Disclosures between TCFD and non-TCFD Supporters

The table presents the regression results of firm-level climate change disclosure for TCFD supporting companies before and after the publication of TCFD recommendations in June 2017. The dependent variable, $CCSS_{t+1}$, is the aggregate climate change exposure variable at year $t+1$. $Post_t$ is a dummy variable, equal to one for firm-year observations after June 2017 and zero otherwise. Control variables are firm size ($Size_t$), market-to-book ratio (MTB_t), return on asset (ROA_t), leverage ratio ($Leverage_t$), property, plant and equipment (PPE_t), and capital expenditure ($Capx_t$). Column (1) is estimated on the full sample whereas column (2) on the subset of firm-years with positive $CCSS$. All variables are defined in the Appendix. The t -statistics in parentheses are adjusted by standard errors clustered at the firm level. *, **, *** represent the 10%, 5% and 1% significance level, respectively.

	[1]	[2]
TCFD Supporter* $Post_t$	0.194*** (3.99)	0.227*** (3.66)
TCFD Supporter $_t$	0.335*** (3.20)	0.386*** (3.79)
$Size_t$	1.120*** (10.57)	0.853*** (7.46)
MTB_t	0.03 (0.70)	-0.005 (-0.10)
ROA_t	-0.111*** (-2.75)	-0.011 (-0.20)
$Leverage_t$	-0.174*** (-3.00)	-0.216*** (-3.01)
PPE_t	0.507*** (4.52)	0.353*** (3.16)
$Capx_t$	-0.088 (-1.34)	-0.179** (-2.39)
$CarbonEmission_t$	0.707*** (5.71)	0.706*** (5.23)
Sample	Full sample	CCSS > 0
Country FE	Yes	Yes
Industry*Year FE	Yes	Yes
Observations	17,420	9,556
Adjusted R2	0.57	0.48

Table IA. IV: Firm-level Climate Disclosure around New Climate Disclosure Policies

This table reports the results of two validation tests relating to our disclosure variable – CCSS – based on the changes in CCSS around the passage of Article 173 in France and EU NFR Directive in EU countries. Panel A presents the regression results of firm-level climate change disclosure for firms around the passage of Article 173 in 2015. The dependent variable is firm-level CCSS. *IOFrance* is the percentage of equity ownership held by French institutional investors in our sample and *Post_{Article 173}* is a dummy variable, which is equal to one from 2015 onwards and zero otherwise. Panel B shows the regression results of the effects of EU NFR Directive on climate change disclosure score. *Treat* equals one if a firm is in France and the UK and has more than 500 employees and more than EUR 20 million in total assets (or EUR 40 million in revenue), and zero otherwise for other firms from Australia, Canada and the US. *Post_{EU NFR}* is a dummy variable, which is equal to one from 2014 onwards, and zero otherwise. We perform a nearest neighbour matching method and one-to-one matching for both treatment and control groups in 2013 year, the most year before the passage of EU NFR Directive. All coefficient estimates are multiplied by 100. All variables are defined in the Appendix. *, **, *** represent the 10%, 5% and 1% significance level, respectively. The *t-statistics* in parentheses are adjusted by standard errors clustered at the firm level.

	Panel A: Article 173		Panel B: EU NFR Directive	
	[1]	[2]	[3]	[4]
<i>IOFrance</i> * <i>Post_{Article 173,t}</i>	0.382*** (5.80)	0.363*** (4.44)		
<i>Treat</i> * <i>Post_{EU NFR,t}</i>			1.436*** (6.87)	1.390*** (11.32)
<i>IOFrance_t</i>	-0.141 (-1.25)	-0.135 (-0.87)		
<i>Size_t</i>	0.293 (1.39)	0.019 (0.07)	-0.038 (-0.08)	-0.055 (-0.14)
<i>MTB_t</i>	0.003 (0.06)	-0.04 (-0.45)	-0.035 (-0.20)	-0.116 (-0.81)
<i>ROA_t</i>	-0.063* (-1.69)	-0.097** (-2.04)	-0.179 (-1.47)	-0.064 (-0.87)
<i>Leverage_t</i>	-0.059 (-0.83)	-0.043 (-0.32)	0.039 (0.11)	-0.021 (-0.11)
<i>PPE_t</i>	0.290* (1.95)	0.208 (0.96)	1.639*** (4.62)	0.576* (1.79)
<i>Capx_t</i>	-0.087 (-1.31)	-0.199** (-2.20)	-0.683** (-2.38)	-0.118 (-0.99)
<i>CarbonEmission_t</i>	0.485*** (3.33)	0.518*** (2.89)	0.366 (0.99)	0.772*** (3.15)
Sample	Full sample	CCSS >0	Matched Sample with replacement	Matched Sample without replacement
Industry*Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	16,562	8,748	4,949	4,845
Adjusted R2	0.80	0.70	0.86	0.74

Table IA. V: Dynamic Treatment Effects of Article 173 and EU NFR Directive on Firm-level Climate Disclosure

This table reports a modified DiD regression model by expanding Equations (1) and (2) to include additional time period dummy variables and their respective interactions with *IOFrance* for Equation (1) and *Treat* for Equation (4). We use a nine-year window (from four years before to four years after the shock) for both climate policies around the passage of Article 173 and EU NFR Directive. We also perform a nearest neighbour matching method and one-to-one matching with replacement for both treatment and control groups in 2013 year, the most year before the passage of EU NFR Directive. All control variables are the same as those used in Table IA. IV. The *t*-statistics in parentheses are adjusted by the clustered standard error at the firm level. All coefficients have been multiplied by 100. *, **, *** represent the 10%, 5% and 1% significance level, respectively.

	[1]	[2]
Year2011*IOFrance	-0.238** (-2.41)	
Year2012*IOFrance	-0.098 (-1.15)	
Year2013*IOFrance	-0.11 (-1.59)	
Year2015*IOFrance	0.035 (0.59)	
Year2016*IOFrance	0.061 (0.53)	
Year2017*IOFrance	0.420*** (4.23)	
Year2018*IOFrance	0.510*** (5.14)	
Year2019*IOFrance	0.566*** (4.65)	
Year2010*Treat		0.512 (1.42)
Year2011*Treat		-0.01 (-0.05)
Year2012*Treat		0.173 (1.06)
Year2014*Treat		0.522** (2.10)
Year2015*Treat		0.960*** (3.26)
Year2016*Treat		1.402*** (4.73)
Year2017*Treat		1.562*** (4.32)
Year2018*Treat		2.450*** (6.71)
Controls	Yes	Yes
Constant	Yes	Yes
Industry*Year FE	Yes	Yes
Firm FE	Yes	Yes
Observations	15,394	4,517
Adjusted R2	0.810	0.853