Climate Risk Disclosures:

Risk Exposure or Enhanced Transparency

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Abstract

Using over 200,000 annual reports from 26 countries/regions between 2008 and 2022, this study develops a measure of climate change disclosure based on alignment with Task Force on Climate-related Financial Disclosures (TCFD) recommendations. Results indicate that higher disclosure levels are associated with lower future risk-adjusted returns, increased liquidity, reduced uncertainty, and a lower implied cost of equity. We do not find significant association between climate change disclosure and future earnings announcement returns, but a positive relationship between climate change disclosure and abnormal returns around events reinforcing environmental policy. Overall, enhanced climate disclosures appear to reduce firms' exposure to climate-related risks.

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I. Introduction

In recent years, investors have become increasingly concerned about the impact of climate change on firms' operating costs and cash flows (e.g., Krueger, Sautner and Starks (2020), Giglio, Kelly and Stroebel (2021)). The growing awareness has increased investors' demand for more climate change information (Krueger, Sautner and Starks (2020)). However, the valuation impact of corporate climate change disclosures remains unclear.

On the one hand, more discussions about climate change in corporate disclosures may suggest greater exposure to climate change risk (Sautner, Van Lent, Vilkov and Zhang (2023)). Meanwhile, a large body of literature documents the existence of a climate risk premium (e.g., Bolton and Kacperczyk (2023), Hsu, Li and Tsou (2023)). Therefore, climate change disclosures should be positively correlated with firms' expected returns if they capture firms' exposure to climate change risk. We label this argument as the *Risk Exposure Hypothesis*.

On the other hand, increasing climate change disclosures improves corporate transparency, which is associated with a lower cost of capital (Dhaliwal, Li, Tsang and Yang (2011)). Ilhan, Krueger, Sautner and Starks (2023) also argue that investors value climate change disclosure and are more willing to increase their holdings in firms with better disclosures due to social norms and liquidity concerns. In this regard, climate change disclosures can help investors develop an informed understanding of firms' risk exposure to climate change and adjust their assessment of uncertainty regarding future performance. Consequently, climate change disclosures should be negatively correlated with firms' expected returns if they represent firms' transparency regarding climate policy and actions. We label this argument as the *Transparency Hypothesis*.

One challenge in testing the two above hypotheses above is to construct an appropriate measure of corporate climate change disclosure. In this study, we use a bag-of-word approach in textual analysis and create an enriched vocabulary using climate-related narratives aligned

with TCFD recommendations from TCFD supporters[1]. Following Engle et al. (2020) and Gentzkow, Kelly and Taddy (2019), we match climate change vocabulary with texts from other firms' annual reports and then employ a term-weighting approach (i.e.*tf-idf*) to capture informative content. The firm level climate change disclosure score (CCDS) is calculated using a cosine similarity function between climate change vocabulary and firms' annual report.[2] This approach has two advantages. First, the bag-of-word method is transparent and consistent with the existing studies in this area (e.g., Li et al. (2024), Sautner et al. (2023)), making our results easily comparable with the previous evidence. Second, TCFD provides clear reporting guidelines. TCFD (2017) emphasizes that disclosures aligned with TCFD recommendations, particularly under the Strategy category, are crucial for investors to assess how vulnerable firms are to physical and transition risks.[3] Using climate change disclosures from TCFD supporters as a benchmark, our climate change disclosure measure not only captures quantity of the climate change discussion, but also incorporates the information of climate risks and opportunities and their financial implications.

We implement our analyses using a large-scale international sample of 26 countries and regions (hereafter countries) from 2008 through 2022. We start with tests to validate our climate change disclosure measure. First, we show that CCDS and the percentage of firms disclosing climate change information are higher in the Utilities, Energy, and Real Estate industries, which are presumably vulnerable to climate risks. At the country level, France exhibits the highest CCDS and the percentage of firms disclosing climate change information whereas the USA exhibits relatively lower levels of climate change disclosure. This variation

[1] Although the TCFD was taken over by the International Sustainability Standards Board (ISSB) in 2023, the ISSB's IFRS S1 and S2 *Climate-related Disclosures* standard fully incorporates the TCFD's structure and four core categories, ensuring continuity while embedding the framework into a globally accepted financial reporting standard. https://www.ifrs.org/news-and-events/news/2023/07/foundation-welcomes-tcfd-responsibilities-from-2024/

[2] We provide more details in Section 2.3 and Online Appendix (OA) IV.

[3] TCFD (2023) shows that several climate disclosure regimes have incorporated the TCFD recommendations into their requirements and guidelines, including the Carbon Standards Disclosure Board (CDSB), Carbon Disclosure Project (CDP), and the EU Corporate Sustainability Reporting Directive (CSRD).

aligns with the climate regulations in both countries[4]. Second, since CCDS builds upon vocabulary aligned with TCFD recommendations, we demonstrate that firms supporting TCFD recommendations have higher CCDS scores after the launch of TCFD recommendations in June 2017. Third, we further verify climate-related contents of our disclosure measure and find that the CCDS measure is positively associated with total carbon emissions and climate risk exposure developed by Sautner et al. (2023), as well as environmental performance rating. This suggests that firms with high CCDS manage their environmental policy well despite their high carbon nature. Lastly, we employ Article 173, which mandated climate disclosure for both listed firms and institutional investors in France, as an exogenous shock to firm-level climate change disclosures. Using a difference-in-difference (DiD) approach, we find that firms with high equity ownership by French institutional investors show increased CCDS in annual reports following Article 173 which supports the validity of our climate change disclosure measure.

Next, we explore how climate change disclosures are associated with future stock returns. Our findings show that portfolios with low (high) CCDS earn high (low) risk adjusted returns in the next year. Using the Fama-French five-factor model, we find that low CCDS firms earn 0.43% more than high CCDS firms per month in global sample and 0.65% per month in the US sample. The results remain robust using Fama and MacBeth (1973) regressions and controlling for various firm characteristics.

Although the evidence from the cross-sectional return test is consistent with the *Transparency Hypothesis*, it is possible that investors initially fail to price climate change risk. Consequently, firms with high climate change exposure experience lower returns in the future

[4] For example, as early as 2001, the French Parliament enacted the *New Economic Regulations,* which require listed companies to set out and report the measures taken to address the environmental and social impacts of their activities in their annual reports. *The Grenelle II Act* in 2010 further requires large companies to increase disclosure of their commitment to sustainable development. *The Energy Transition Law* in 2015 strengthened climate change disclosure for listed companies and introduced requirements for institutional investors to disclose information on climate change. In contrast, there have not yet been mandatory ESG or climate-related regulations in the USA during our sample period.

as investors adjust their beliefs and correct the valuation of these firms. For example, Hong, Li and Xu (2019) show that firms with a higher drought risk as measured by the Palmer Drought Severity Index have subsequent lower average returns. Görgen et al. (2019) build upon ESG variables to construct a brown-green score as a proxy for transition risks. They show that firms with more exposure to transition risks earn lower returns than firms with less exposure, inconsistent with a risk premium.

We then examine the relationship between CCDS and firms' liquidity and uncertainty. Under the *Transparency Hypothesis*, firms with high CCDS should be more liquid and investors should face less uncertainty when investing these firms. In contrast, if the *Risk Exposure Hypothesis* holds and the market mispriced high CCDS firms, then CCDS firms should exhibit lower liquidity and higher uncertainty in the future. We use three measures of liquidity including bid-ask spread, Amihud's Illiquidity (*AIM*), and the number of zero return days (ZeroRet), and two measures of firms' uncertainty including return volatility and absolute forecasting errors. The results consistently show that high CCDS firms are more liquid and face less uncertainty across all measures. In addition, we find that CCDS is insignificantly correlated with future earnings announcement results and negatively correlated with firms' implied cost of equity. All the evidence further lends support to the *Transparency Hypothesis*.

One potential caveat of the CCDS measure is that the TCFD guideline was made publicly available in 2017 which may induce look ahead bias in our early sample.[5] In addition, omitted variables, such as other information quality variables, may influence the results. First, we confirm that our results hold in a sample using observations starting from 2017. Next, we conduct six event studies including *the 2016 U.S. president election*, the 2020 *U.S. president election, the 2022 SEC climate reporting proposal*, *the 2024 SEC Climate Reporting Final Rules*, *the 2014 EU Non-Financial Reporting-Directive (NFRD)*, and *the 2020 EU Climate*

[5] We do not aim to provide a predictive trading strategy in this study.

Law. These events span from 2014 through 2024 and are largely exogenous. The result of the 2016 U.S. president election (other five events) weakens (strengthens) the perception of environmental policy. If CCDS represents high exposure to climate change, we should expect that firms with high CCDS experience high (low) event returns for the event weakening (strengthening) the perception of environmental policy (*Risk Exposure Hypothesis*). In contrast, *Transparency Hypothesis* predicts a negative (positive) associate between event returns and firms' CCDS for the event weakening (strengthening) the perception of environmental policy supports. Again, our results are consistent with the prediction of *Transparency Hypothesis* and the short-window event study covering a variety of time periods mitigates the concerns about look ahead bias and omitted variables. In sum, our collective evidence supports the arguments that climate change disclosures enhance transparency and are associated with low climate change risk exposure.

This paper contributes to the literature of climate change disclosure (e.g., Sautner et al. (2023), Li et al. (2024)). Distinct from Sautner et al. (2023) and Li et al. (2024) who use earnings calls as the primary source of climate change disclosure, we focus on corporate annual reports. While earnings calls are rich and flexible sources of voluntary information communication, corporate annual report has its unique advantages in studying climate change disclosure, especially in a global setting. First, annual reports have wide coverage of firms without selection bias and the information in annual reports is more credible than that in earnings calls because of assurance and high litigation risk. Second, as indicated by Lin, Shen, Wang, and Yu (2024), the majority of countries mandate climate disclosures in an integrated approach, which leads to more comprehensive climate change disclosures in annual reports. Besides, we employ TCFD recommendations as a benchmark to develop the vocabulary. Since the TCFD recommendations focus on material climate-related financial information, this approach allows us capturing valuable climate change disclosures. Our evidence complement

the existing literature by showing that financial relevant climate change disclosures are associated with better transparency and lower cost of capital. Our results also highlight the importance to consider alternative approach in measuring climate change disclosures.

This study also extends previous research investigating the financial implications of nonfinancial disclosures. Ioannou and Serafeim (2019) examine ESG disclosure mandates in four countries and document that increase in ESG disclosures increase firm valuation. Krueger, Sautner, Tang and Zhong (2024) find similar results by showing that global ESG disclosure mandates contribute to an improvement in stock liquidity. However, Gibbons (2024) documents that mandatory nonfinancial disclosures do not affect stock liquidity and firm valuation. Our study focuses specifically on climate change disclosures, offering a more targeted lens to assess their financial implications in an international setting. We find that climate change disclosures help to reduce information asymmetry, leading to a reduced cost of equity and increased stock liquidity. These findings align with Krueger, Sautner and Starks (2020), who highlight the importance of climate change disclosures to investors.

The remainder of this paper is organized as follows. Section II describes the sample construction and data and Section III reports the summary statistics and main results. Section IV provides further potential explanations for the return predictability of climate change disclosures and Section V provides several robustness tests. Section VI concludes this paper.

II. Sample and Data

A. Sample Formation

We begin with a primary international sample consisting of 26 countries, each of which is required to have at least ten publicly listed TCFD supporting firms by the end of 2022. To identify publicly listed TCFD supporters, we obtain an initial list of organizations that support

TCFD recommendations from TCFD websites[6]. Of these supporters, we delete some organizations (e.g., industry associations and governments) that are not companies. We then perform fuzzy matching through TCFD supporters' names and verify matched listed companies using additional industry and location information. Figure 1 shows that Japan has the highest number of publicly listed TCFD supporting companies around the world[7], far more than any other countries. The Online Appendix (OA) I shows more details on the identification of listed TCFD supporting firms and OA II provides a sample of 26 countries, including Australia, Brazil, Canada, China, Denmark, Finland, France, Germany, Hong Kong, India, Italy, Japan, Mexico, Netherlands, Norway, Philippines, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Turkey, United Kingdom, and United States.

To minimize the survivorship bias, we combine all active and dead publicly listed stocks in each country from constituent lists provided by WorldScope and Datastream, and apply the screening procedures (e.g., Ince and Porter (2006), Griffin, Kelly and Nardari (2010) and Krueger et al. (2024)) to create our firm sample. Details on the screening procedures are presented in OA II.

B. Data Source

To construct a measure of firm-level climate change disclosures, we obtain international firms' annual reports from 26 countries between fiscal year 2008 and 2022 from Refinitiv Global Filings, which provides comprehensive coverage of annual reports for over 130 countries around the world. These annual reports can be downloaded from Refinitiv Knowledge Direct API (RKD) (Lin et al. (2024)). All annual reports in PDF format will be

[6] The list of TCFD can be accessed via https://www.fsb-tcfd.org/supporters/.

[7] One reason is that in May 2019, the Ministry of Economy, Trade and Industry (METI), the Ministry of the Environment (MOE), and the Financial Services Agency of Japan (FSA) in Japan led the establishment of a public-private partnership organization, the TCFD Consortium. The TCFD Consortium brings together institutional investors, financial institutions, and commercial companies in Japan to promote TCFD disclosure. Another reason is that the Tokyo Stock Exchange requires companies listed in the "Primary Market" segment, from April 2022, to fully comply with climate disclosure requirements aligned with the TCFD recommendations (TCFD (2022)).

first parsed into text format. Details on parsing and cleansing annual reports are provided in OA III. The annual reports of the US firms (i.e., 10-K filings) can be gathered from the Securities and Exchange Commission Electronic Data Gathering, Analysis, and Retrieval (SEC EDGAR)[8].

Our sample consists of firms with climate change disclosure scores that exist in a combination of multiple databases. We obtain stock price and trading data from Compustat Global and CRSP, accounting data from Compustat, financial analysts and earnings forecast data from I/B/E/S, firm-level ESG performance data from LSEG ESG, and institutional ownership data from Factset. Following previous literature, we exclude financial firms with SIC codes between 6000 and 6999. Firm-year observations with negative book equity values or total assets are also dropped. The final sample includes 14,994 unique firms with 126,727 firm-year observations between fiscal years 2008 and 2022. Table 1 demonstrates the procedures of how we create our final sample.

C. Measure of Climate Change Disclosure

Textual analysis has been widely adopted in accounting and finance research for extracting qualitative insights from corporate reports, such as document similarity, text readability, and narrative sentiment (Loughran and McDonald (2016)). Instead of analyzing these generic linguistic features, our study focused on firm-level climate change information disclosure. We employ a bag-of-word approach in natural language processing, which allows us to systematically capture climate-specific information disclosed by firms. This method is used in Engle et al. (2020), which computes a market-wide climate risk exposure using news articles, and also Sautner et al. (2023) which calculates firm-level climate change exposures using earnings conference calls. Specifically, the estimation process of our firm-level climate change disclosure measure involves three main steps: (1) developing a comprehensive and

[8] The raw and cleansed 10-K filings can also be obtained from Loughran-McDonald website.

unique climate change vocabulary as the reference for textual analysis; (2) extracting parsed and cleansed texts that are potentially relevant to climate change from firms' annual reports[9]; 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. We denote the firm-level climate change similarity score as CCDS throughout our empirical analysis. The detailed discussion about the estimation of CCDS measures is presented in OA IV.

A common concern when applying TCFD-based climate change vocabulary to firms' annual reports predating the publication of TCFD recommendation in 2017 is about looking-ahead bias and retrospective overfitting. However, such a concern is likely minimal for several reasons. First, the TCFD is a codification, not creation of new climate disclosure concepts. Instead, it *standardizes and organizes* terms that already existed in fragmented form. For example, global firms like BHP, discussed climate risk management, carbon pricing, and strategic responses well before TCFD. Second, climate change vocabularies are measurement tools rather than predictors. Our aim is not to assert that firms were TCFD-compliant before 2017, but to assess the presence of TCFD-aligned concepts in their disclosures. Third, climate change vocabularies are analogous precedent in finance and accounting regarding textual analysis. For instance, Matsumura, Prakash and Vera-Muñoz (2024) apply SASB materiality maps to 10-K filings from periods predating SASB's official release in 2011. The Loughran-McDonald dictionaries, developed in the 2010s, are widely used to analyze financial sentiment in documents from the 1990s or earlier (Loughran and McDonald (2011)).

[9] We acknowledge that stand-alone ESG reports may contain relevant climate change information, and omitting them could potentially lead to an underestimation of disclosure scores for certain firms. However, we believe that such an omission does not materially affect our results for two reasons. First, the prevalence of separate ESG reports is relatively low. According to Lin, Shen, Wang and Julia Yu (2024), only 3.3% of firms issue separate ESG reports, suggesting that excluding them affects only a small subset of our sample and is unlikely to bias our main findings. Second, annual reports are subject to stringent regulatory and financial auditing standards. In contrast, stand-alone ESG reports are typically voluntary, unaudited and vary widely in structure and formats. Even among firms that do issue ESG reports, only about one-third obtain third-party assurance (Gipper, Ross and Shi (2025)), raising concerns about the reliability of disclosed information they contain.

The CCDS measures firm-level climate change concepts aligned with TCFD recommendations in annual reports. The TCFD provides a globally recognized framework to link climate-related risks and opportunities to financial implications. The framework is structured around four key categories, including Governance, Strategy, Risk Management, and Metrics and Targets, each offering insights into a firm's climate resilience and adaptability (TCFD (2017)). Figure 2 shows the recommended disclosures under four categories.

Climate governance by corporate boards is the foundational building block of effective climate risk and opportunity management. Firms with strong governance demonstrate higher resilience and lower risk profiles (Eccles, Ioannou and Serafeim (2014)). For example, governance mechanisms embedding climate consideration into business decisions reduce exposures to regulatory risks (Kölbel, Heeb, Paetzold and Busch (2020)). The TCFD's focus on strategy relates to how climate change impacts business models, competitive positioning, and long-term financial planning. Eis et al. (2019) document that climate risks have profound effects on both upstream firms themselves and downstream markets through multiple channels, such as operations, supply chain, technological advancement and regulatory changes. Strategic disclosures allow investors to predict cash flow variations better and adjust risk premiums accordingly (Giglio, Kelly and Stroebel (2021)).

Effective climate risk management disclosures outline how a firm identifies, evaluates, and mitigates physical and transition risks. Studies show that superior risk management on environmental issues can reduce financing costs and increase firm values (e.g., Sharfman and Fernando (2008), Albuquerque, Koskinen and Zhang (2019)). Central to risk management, risk materiality identification is particularly relevant to investors since firms are required to disclose what really matters, alleviating information overload. Metrics and targets provide quantitative benchmarks for evaluating a firm's climate-related performance. Eccles, Serafeim and Krzus (2011) highlight that among environmental metrics, equity investors pay close attention to

carbon emissions, reflecting their concerns about the impacts on equity values. Standardized metrics also improve comparability and drive accountability (Clark, Feiner and Viehs (2015)). For instance, consistent disclosure of carbon intensity measures enables investors to price carbon-related risks effectively. Ioannou, Li and Serafeim (2016) show that setting carbon emissions reduction targets acts as an effective motivating tool to mitigate a firm's exposure to material climate change.

Table 2 reports the distribution of firm-level CCDS by years, countries, and sectors. Panel A shows that firm-level climate change disclosure scores experienced a significant increase between fiscal years 2008 and 2022. The percentage of firms disclosing climate change information in annual reports also rose from 15% in 2008 to 67% in 2022. Panel B shows the distribution of CCDS by countries where France has the highest average CCDS value and the second highest percentage (68.28%) of firms reporting climate change information in the world. In contrast, the US exhibits a relatively low average CCDS and a percentage (31.98%) of firms with CCDS greater than zero, which is consistent with Eccles, Serafeim and Krzus (2011) who argue that there is considerable climate change skepticism in the US[10]. Panel C of Table 2 shows the variations of CCDS across sectors. The Utilities, Energy, and Real Estate industries have higher levels of climate change disclosures, of which the Utilities sector exhibits the highest average CCDS value and the highest percentage of firms reporting climate change information. This aligns with the intuition that these industries are more vulnerable to the financial impacts of climate risks.

D. Summary Statistics

Table 3 shows pooled summary statistics of the variables of interest. Specifically, we report the mean (Mean), median (Median), standard deviation (Std.Dev), 25th percentile (P25),

[10] Our untabulated results show that over 63% of the US companies in the 2022 year disclose climate change information in annual filings, an increase of 24% relative to the 2019 year. This is presumably due to the SEC's proposed climate reporting rules.

75th percentile (P75) of the variables, as well as the number of non-missing observations for each variable. We have a total of 126,727 firm-year observations with non-missing CCDS values. Our main variable, CCDS, is firm-level climate-related financial disclosures through textual analysis of global annual reports. The average value of CCDS is 0.042 with 39.82% of firm-year observations showing CCDS greater than zero. The main control variables include total asset (*LogAT*), book-to-market ratio (*LogBM*), return on asset (*ROA*), leverage ratio (*Leverage*), capital expenditure (*Capx*), property, plant and equipment (*PPE*), dividend indicator (*Dividend*), return on equity (*ROE*), Whited and Wu index (*WWIndex*) to measure financial constraints. We also introduce other variables for validation tests, including TCFD supporter indicator (*TCFDSupporter*), the number of analysts (*#Analyst*), the percentage of ownership by French institutional investors (*IOFrance*), ESG score (*ESGScore*), environmental scores (*EnvironmentalScore*), total carbon emission (*LogEmission*), emission intensity (*EmissionIntensity*), climate change exposure ($CC^{exposure}$) and risk (CC^{risk}) measures by Sautner, Van Lent, Vilkov and Zhang (2023). Notably, only 33% of companies with CCDS available have $CC^{exposure}$ and CC^{risk} data constructed based on earnings conference calls. This is consistent with Nagar and Schoenfeld (2024) arguing that earnings conference calls are available in only approximately half of global listed firms. All variable definitions can be found in Appendix 1. All continuous variables are winsorized at 1% and 99% levels to alleviate the effects of extreme values.

Figure 3 presents the correlation matrix of the variables shown in Table 3. The color indicates the sign of correlation coefficients for which the blue represents the negative correlation and the red represents the positive correlation. The color darkness represents the strength of the correlation. We find that *CCDS* is not highly correlated with other variables, except for *ESGScore* and *EnvironmentalScore* with correlation coefficients of 0.43 and 0.46,

respectively. In particular, the correlation between *CCDS* and $CC^{exposure}$ and CC^{risk} is relatively low at 0.27 and 0.20, respectively.

E. Validation Tests

As presented in Table 2, the CCDS captures some variations across countries and industries, which partially validates the disclosure measure. Next, we perform several tests to strengthen the validity of the CCDS. Since our disclosure measurement relies on climate change vocabulary based on TCFD-aligned texts from TCFD supporters, we expect TCFD supporters to have higher CCDS after the launch of TCFD recommendations in the 2017 year. To examine this hypothesis, we estimate the following regressions:

$$CCSS_{i,t} = \alpha + \beta TCFDSupporter \times Post_{i,t} + \gamma' Controls_{i,t} + Fixed\ Effects + \varepsilon_{i,t} \quad [1]$$

TCFDSupporter is an indicator variable that equals one for TCFD supporting firms and zero for non-TCFD supporting firms. *Post* is equal to one for observations following the launch of TCFD recommendations in 2017 and zero otherwise. Following Fiechter, Hitz and Lehmann (2022) and Ilhan, Krueger, Sautner and Starks (2023), we include the natural logarithm of total assets (*LogAT*), the natural logarithm of book-to-market ratio (*LogBM*), return on assets (*ROA*), leverage ratio (*Leverage*), property, plant and equipment scaled by total assets (*PPE*), capital expenditure scaled by total assets (*Capx*), dividend indicator (*Dividend*) and the number of analysts following the firm (*#Analysts*) as control variables. We saturate the model with firm and year fixed effects to account for possible unobservable heterogeneities in firm characteristics and year-specific trends in climate change disclosures. The standard errors are clustered at the country level. As shown in Table OA4, the estimated coefficient of *TCFDSupporter*×*Post* is significantly positive in column (1), suggesting that TCFD supporters disclose more climate change information after the publication of TCFD recommendations. The magnitude means that climate change disclosures increase by 0.012 for firms becoming

TCFD supporters compared to non-TCFD supporting firms after the launch of TCFD recommendations, an economically sizable effect compared to the CCDS mean of 0.042. The magnitude of the effect is stronger for sample firms with CCDS greater than zero in column (2). The result also persists during the two-year balanced window before and after the launch of TCFD recommendations in column (3).

Next, we examine the climate-related information contents of our disclosure measure by linking CCDS to several variables related to climate change in the following regression:

$$CCSS_{i,t} = \alpha + \beta CCVariables_{i,t} + \gamma' Controls_{i,t} + Fixed\ Effects + \varepsilon_{i,t} \quad \textbf{[2]}$$

CCVariables represents a set of variables related to climate risks, including the natural logarithm of total carbon emission (*LogEmission*), total carbon emission scaled by firm's revenue in US dollar (*EmissionIntensity*), ESG scores (*ESGScore*), environmental scores (*EnvironmentalScore*), and climate change exposure ($CC^{exposure}$) and risk (CC^{risk}) measures developed by Sautner et al. (2023). Controls are those specified in Equation (1) and (2). The firm and year fixed effects are included and the standard errors are clustered at the country level. In Table OA5, we find that CCDS is positively correlated with firm-level carbon emissions in columns (1)-(2) and climate change exposures in columns (5)-(6), and also environmental performance in columns (3)-(4). The magnitudes are meaningful, for example, a one-unit standard deviation increase in *LogEmission* is associated with 1.724% increase in CCDS which accounts for 41% of the sample mean of *CCDS*. These results suggest that CCDS reflects information pertinent to climate risks and also more effective climate risk management.

We further strengthen the validation test of CCDS by examining the changes in *CCDS* around an exogenous policy shock. 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 change disclosure directly through mandated reporting requirements and indirectly through an elevated demand for climate change information from their investors (Ilhan et al. (2023)). Therefore, we anticipate a significant increase in *CCDS* for companies held by French institutional investors following the passage of the regulation in August 2015. We introduce a variable, *IOFrance*, representing the firm's equity ownership held by French institutional investors, and a dummy variable, $Post_{Article\ 173,t,}$ which is equal to one for the year 2015 and beyond, and zero otherwise. Second, we use exogeneous staggered mandatory ESG reporting across countries for identification. These mandatory initiatives would presumably result in a higher level of climate change disclosures. $Post_{Mandatory\ ESG}$ is a dummy variable which equals one for all years after a country adopts a mandatory ESG disclosure regulation at year t and otherwise zero. The mandatory ESG disclosure regulation data is from Krueger et al. (2024). We then estimate the following difference-in-difference (DiD) regressions:

$$CCSS_{i,t} = \alpha + \beta_1 IOFrance_{i,t} \times Post_{Article173,t} + \beta_2 IOFrance_{i,t} + \Upsilon' Control_{i,t} + Fixed\ Effects\ + \varepsilon_{i,t} \quad \textbf{[3]}$$

$$CCSS_{i,t} = \alpha + \beta_1 Post_{Mandatory\ ESG,t} + \Upsilon' Control_{i,t} + Fixed\ Effects\ + \varepsilon_{i,t} \quad \textbf{[4]}$$

The control variables are the same as those specified in Equation (1). We include firm and year fixed effects in both regressions to account for possible unobservable heterogeneities in firm characteristics and year trends in climate change disclosures. The standard errors are clustered at the country level.

Table OA6 reports the DiD regression results of firm-level climate change disclosures around *Article 173*. Column (1) shows a consistently positive and significant coefficient on $IOFrance \times Post_{Article\ 173}$, suggesting that firms with a high level of French institutional ownership effectively responded to the introduction of Article 173 by increasing climate change disclosures. As *Article 173-VI* mandates French listed firms to disclose climate change information in their annual reports, potentially introducing a confounding shock to climate

change disclosures by French firms, we exclude French listed firms in column (2) and continue to find a significantly positive effect of *IOFrance*. The results also hold for a sample of firms with positive *CCDS* scores in column (3). Additionally, we focus on firms with large French institutional ownerships of at least 3% in column (4) and find that the magnitude of the effect is stronger relative to column (1).

Table OA7 presents the estimated effects of mandatory ESG disclosure regulations on climate change disclosures using three different DiD approaches, Two-way Fixed Effects (TWFE), Callaway and Sant'Anna (2021) and stacked DiD. Across all estimators and sample specifications, $Post_{Mandatory\ ESG}$ shows a consistently positive and statistically significant effect on climate change disclosure. These results suggest that the introduction of mandatory ESG regulations leads to a meaningful increase in firms' climate change disclosures. Figure OA2 illustrates the dynamic effects of staggered mandatory regulation across countries on climate change disclosures. There are no statistically significant differences in *CCDS* between treated and control firms prior to the implementation of mandatory ESG regulations, suggesting the presence of undifferentiated pre-trends. Following the adoption of mandatory ESG disclosure requirements, a sharp increase in *CCDS* among treated firms appears. Overall, our validation tests confirm the reliability of CCDS in capturing firm-level material climate change disclosures.

III. Firm-level Climate Change Disclosure and Stock Returns

This section focuses on the central analysis that examines the link between climate change disclosures and future stock returns. Firstly, we perform the time-series factor pricing model using CCDS-sorted portfolio returns to investigate the extent to which the cross-sectional variations in returns can be explained by the five Fama-French factors (Fama and French

(2015)) in the US and global samples[11]. Next, we conduct FM cross-sectional regressions (Fama and MacBeth (1973)) to test the predictability of climate change disclosures for stock returns. This enables us to explore the disclosure-return link at the firm level and control for a larger set of firm characteristics compared to the common risk factors.

A. Baseline Results of Sorting Portfolios

To investigate the relationship between climate change disclosures and stock returns, we create three portfolios sorted on CCDS based on the breakpoints from big stocks. More specifically, stocks without climate change disclosures are classified into one group in June of each year[12], generating a portfolio with zero CCDS. Second, we allocate stocks with positive CCDS into two groups based on the median market capitalization in June of each year. Then CCDS breakpoints are the 30th and 70th percentile from big size stocks, with these applied to all CCDS stocks in the US and global samples. The CCDS sorting method conditional on big size stocks is consistent with sorting BM ratios, profitability, and investment ratios in Fama and French (2015, 2017). This conditionally produces three portfolios with low, medium, and high CCDS. After formatting the four portfolios (i.e., Zero, Low, Medium, and High), we calculate the value-weighted monthly returns on these portfolios from July of year t to June of next year $t+1$. To investigate the disclosure-return relationship, we create two portfolios: Low-High and Zero-High that involve taking long positions on low (Zero) CCDS stocks and short positions on high CCDS stocks, and calculate the monthly value-weighted returns on two portfolios.

Table 4 reports the time-series average value of key firm characteristics across portfolios sorted on CCDS for different samples. We find that firms with higher climate change

[11] The five factor data for the US sample is available from the Kenneth R. French library. The factor construction for non-US global sample is detailed in Appendix OA VI.

[12] Firms with fiscal years ending in March or April usually release their annual reports after June. As a consequence, we use the most recent available CCDS value based on the release dates when creating portfolios. This approach ensures that our analysis incorporates the most up-to-date data available in June.

disclosures are larger, and have higher leverage ratios, tangibility, profitability, dividend payment, and lower financial constraints.

Table 5 reports the mean and t-statistics of excess returns for portfolios sorted on CCDS in the global, US and non-US samples, respectively. We find a consistent pattern in all samples where the average monthly excess returns from low CCDS to high CCDS portfolios decrease. The low-minus-high portfolios earn a higher return of 0.564% with a *t-statistic* of 3.389 globally, compared to 0.836% with a *t-statistic* of 4.076 in the US sample. Similar results are also found in Zero-High portfolios. This suggests a significant predictive ability of climate change disclosures for stock returns.

Next, we examine the extent to which the variations of returns on portfolios sorted on CCDS are explained by estimating the time-series regressions with the common risk factors for the global sample in Panel A, the US sample in Panel B, and the non-US sample in Panel C, as shown in Table 6. The estimated coefficients of each risk factor indicate the corresponding factor loadings (i.e., betas), and the intercepts in each regression represent the risk-adjusted returns (i.e., alphas) in percentage from the Fama-French five factor model (Fama and French (2015))[13]. The results show that the risk-adjusted returns on three CCDS portfolios are statistically significant and experience a decrease when moving from low CCDS portfolios to high CCDS portfolios. The low-minus-high and zero-minus-high portfolios yield significant annualized alphas of 5.11% (i.e., 0.426%*12) and 5.05% globally, with 7.79% and 5.84% for the US sample, respectively. Therefore, the cross-sectional returns of portfolios sorted on climate change disclosures cannot be explained by the common risk factors.

As firm size plays an important role in stock returns, to further examine whether the CCDS-return patterns persist in different size groups, we employ a double sorting approach for

[13] We also employ the Fama-French five factor plus momentum factor model and the HXZ q-factor (Hou, Xue and Zhang (2015)) model for the US sample. The results on Table OA8 remain robust.

firm size and climate change disclosure scores, generating a total of six portfolios. Within each size group, we construct the low-minus-high portfolios that long low CCDS stocks and short high CCDS stocks and calculate the monthly value-weighted return on each portfolio. In Table OA9, we find that the alphas on the Low-High portfolios are statistically significant in both small and big size groups for the global and non-US samples, which alleviates the concern that return predictability of climate change disclosures is driven by the firm size. By contrast, the significant alpha exists only in big size groups of the US sample in Panel B, with a *t-statistic* of 3.54. This suggests that climate change disclosure to forecast cross-sectional return is not driven by small size stocks, and instead centers on big size stocks that are relatively easy to trade and less likely to have risk premiums related to illiquidity.

B. Fama-MacBeth Regressions

The Fama-MacBeth regression is commonly applied in asset pricing research with the advantage of lower pricing errors (Fama and French (2020)). We run Fama-MacBeth regressions to further test the explanatory power of CCDS to cross-sectional returns at the firm level. Motivated by Daniel and Titman (1997) and Brennan, Chordia and Subrahmanyam (1998), we relate stock returns to a larger list of firm characteristics in FM regressions with the advantage of avoiding error-in-variable (EIV) issues associated with the estimated beta[14] (e.g., Chordia, Goyal and Shanken (2017), Jegadeesh et al. (2019) and Fama and French (2020)).

We specify the dependent variable as the monthly stock return for the subsequent month. In addition, stocks that underperform in the short run could experience positive abnormal returns in the long run, and vice versa (Jegadeesh and Titman (1993)). This raises a potential concern that the negative short-term return predictability we find for climate change disclosures

[14] Jegadeesh et al. (2019) explain that FM regression proceeds in two steps: "the first pass is a time-series regression of individual asset returns on the proposed factors to estimate factor loadings or betas. The second pass regresses the cross-section of asset returns on betas obtained from the first-pass regression. The explanatory variables in the second-pass regressions are beta estimates from the first pass, which estimate true betas with error and therefore have an errors-in-variables (EIV) problem".

may reflect temporary mispricing that reverses over time. In other words, firms with higher climate change disclosures could earn higher future returns, offsetting low short-term returns. To rule out this possibility, we also compute the average monthly return over the subsequent one year as an additional dependent variable[15].

In each month between July 2009 and December 2023, we conduct the cross-sectional regressions of monthly stock return on CCDS and control variables, including the natural logarithm of market capitalization (*LogME*), the natural logarithm of book value scaled by market capitalization (*LogBM*), asset growth rate (*Investment*), return on equity (*ROE*), past twelve-month return momentum (*RetPrior12M*), and return volatility (*RetVolPrior12M*). We also add leverage ratio (*Leverage*) and property, plant and equipment ratio (*PPE*), and the Whited and Wu index (*WWIndex*) (e.g., Görgen et al. (2019), Hsu, Li and Tsou (2023)). Control variables are estimated using the most recent accounting data available in each month. All independent variables are winsorized at the 1st and 99th percentile levels and standardized with zero mean and one unit standard deviation.

The Fama-MacBeth regression results for the US and non-US global samples are reported in Table 7[16]. The coefficients are the average time-series values from monthly cross-sectional regressions, and the corresponding *t-statistics* are adjusted based on the Newey-West standard errors with twelve lags. We find that climate change disclosures are negatively associated with stock returns, with statistically significant coefficients of -0.132 and -0.071 in the US and the non-US global samples, respectively. The estimated coefficients of CCDS suggest that a one-standard-deviation decrease leads to an increase of 1.58% and 0.85% in annualized stock return, respectively. Additionally, we continue to find a significant and negative association between

[15] Our results remain robust when using the average monthly stock return over the subsequent three and six months in Table OA12.

[16] We also conduct pooled regressions with year-month and industry fixed effects, and standard errors double clustered at both the firm and year levels. The results continue to show a significant and negative relationship between climate change disclosures and monthly stock returns across the global, U.S., and non-U.S. samples.

climate change disclosures and future returns in the long term. This evidence contradicts the expectations under a long-term reversal hypothesis, suggesting that the return premium is not a temporary anomaly.

Pukthuanthong, Roll and Subrahmanyam (2019) argue that firm characteristics relate to expected returns, presumably due to being good proxies for factor loadings or arbitrage opportunities. Given a basic concept that higher expected returns are compensated for investors to bear systematic risks measured by factor loadings, we introduce estimated betas as explanatory variables in the Fama-MacBeth regression with firm characteristics. In each month, we calculate betas by regressing stock returns on the Fama-French five risk factors from a time-series rolling window over the past two years with at least 300 daily returns and then address the EIV issues for beta estimates (Chordia, Goyal and Shanken (2017)). Details are discussed in OA VII. Table OA11 shows robust results that climate change disclosures are negatively associated with stock returns and the return predictability of CCDS is not subsumed by the estimated factor loadings.

IV. Potential Explanations

Traditionally, stock return predictability can be understood through two primary channels: the cost of equity and cash flow. The cost of equity affects expected returns by reflecting perceived firm risks, while strong and stable cash flows are likely to correlate with higher expected returns as they signal financial health and growth potential. As explained by Starks (2023), investors can integrate ESG information into their investment decisions as ESG activities have a significant effect on a firm's risk profile and cash flows. Therefore, we base on two channels in this section to explore some potential explanations for the negative relationship between CCDS and cross-sectional returns.

A. The Channel of Cost of Equity

By providing a clear picture of a company's exposure to climate risks and opportunities, climate change disclosures could attract a broader investor base and facilitate trading among market participants, which leads to lower bid-ask spread and greater depth of buy and sell orders (Krueger et al. (2024)). This increased liquidity could contribute to lower liquidity risk premium that investors demand and thereby lower stock return being compensated.

Additionally, Bolton and Kacperczyk (2021) argue that more disclosures can reduce perceived uncertainty facing uninformed investors. They demonstrate that firms with carbon disclosures experience lower stock return volatility and thus lower average stock returns than those without disclosures. To some extent that analyst forecasts influence investors' expectations of future earnings (Lang and Lundholm (1996)), investors may face reduced information uncertainty if analysts issue accurate earnings forecasts for firms with transparent climate reporting.

Higher levels of disclosure can mitigate adverse selection problems by reducing information asymmetry, which leads to a lower cost of capital (e.g., Diamond and Verrecchia (1991), Leuz and Verrecchia (2000)). This also pertains to ESG disclosures (Dhaliwal et al. (2011)). Pástor, Stambaugh and Taylor (2022) document that green stocks have lower expected returns due to a reduced implied cost of capital. This can be attributed to investors' green preference and better management to hedge climate risks (Pástor, Stambaugh and Taylor (2021)). Matsumura, Prakash and Vera-Muñoz (2024) find that firms disclosing climate change information in 10-K filings experience lower firm risk, as measured by implied cost of equity, and therefore lower stock returns.

Hence, a potential explanation for the disclosure-return relationship is that climate change disclosures can lead to higher stock liquidity, lower information uncertainty and a lower cost

of capital. To examine this possibility, we perform several tests by relating CCDS to them in the following regressions.

$$Illiquidity_{i,t+1} = \alpha + \beta CCSS_{i,t} + \gamma' Controls_{i,t} + Fixed\ Effects + \varepsilon_{i,t} \quad \textbf{[5]}$$

$$Uncertainty_{i,t+1} = \alpha + \beta CCSS_{i,t} + \gamma' Controls_{i,t} + Fixed\ Effects + \varepsilon_{i,t} \quad \textbf{[6]}$$

$$COE_{i,t+1} = \alpha + \beta CCSS_{i,t} + \gamma' Controls_{i,t} + Fixed\ Effects + \varepsilon_{i,t} \quad \textbf{[7]}$$

Following Krueger et al. (2024), we measure stock illiquidity using three measures in Equation [5]. *Bid-ask Spread* is computed as the natural logarithm of the median value of the difference between daily closing bid and ask prices divided by the midpoint. Amihud (2002) *illiquidity measure (AIM)* is computed as the natural logarithm of the median value of the daily absolute stock returns divided by daily trading volumes in US dollars. *ZeroRet* is estimated as the number of trading days with zero returns scaled by the potential trading days. These three measures are estimated over the subsequent twelve months starting from four months after the end of the fiscal year. Second, we use stock return volatility and forecast errors to proxy for information uncertainty in Equation [6]. *RetVol* is computed as the standard deviation of stock returns over the subsequent twelve months starting from four months after the end of the fiscal year. *FError (0)* and *FError (1)* denotes the analyst forecast error for the current year and one year ahead. The analyst forecast error is measured as the average value of the absolute difference between analyst mean estimates and actual earnings using I/B/E/S summary file, then scaled by stock price at the beginning of the year. Third, we measure the cost of equity in Equation [7], *ImpliedCOE*, as the median value of four measures from Easton (2004), Gebhardt, Lee and Swaminathan (2001), Claus and Thomas (2001) and Ohlson and Juettner-Nauroth (2005). We include firm and year fixed effects in all models to account for possible

unobservable heterogeneities in firm characteristics and year-specific trends. The standard errors are clustered at the firm level.

Table 8 shows the estimated coefficients on CCDS are significantly negative in all regressions for stock illiquidity measures, indicating that firms disclosing more climate change information have improved stock liquidity reflecting a reduction in information asymmetry. In terms of information uncertainty, climate change disclosures are negatively associated with return volatility and analyst forecast errors, pointing to a lower level of firm risk. We also find that climate change disclosures significantly reduce the cost of capital[17]. Overall, our findings provide compelling evidence for the value of climate change disclosures, showing a clear pathway from disclosures to stock returns. The empirical pathway of higher stock liquidity, lower information uncertainty and lower cost of capital lends the strong and direct support for *Transparency Hypothesis.*

B. The Channel of Cash Flow

Under a rational context, corporate managers with an objective of maximizing firm performance only disclose favorable information (Verrecchia (2001)) as information is not costless. That is, firms may signal their good performance to the market through information disclosures, potentially suggesting an association with cash flows. Recent studies show that ESG information generating positive stock returns can predict firm profitability (Pedersen, Fitzgibbons and Pomorski (2021)). Hsu, Li and Tsou (2023) find that firms emitting toxic pollutants earn higher average returns due to greater exposure to systematic risks related to environmental regimes, and have a higher probability of future profits being affected by changes in policy. Therefore, one explanation for the disclosure-return relationship is that climate change disclosures correlate with firm earnings. To test this possibility, we investigate the cumulative abnormal returns around earnings announcements in the four quarters following

[17] Our results remain robust when using a subsample with CCDS greater than zero in Table OA 13.

CCDS-sorted portfolio constructions. Panel A of Table 9 provides consistent evidence that the cumulative abnormal returns of the low-minus-high portfolios over the windows [-1,3] and [-1, 5] are insignificant. These findings suggest that stocks with different levels of climate change disclosures do not differ regarding firms' earnings.

Dechow, Kothari and Watts (1998) argue that earnings are more informative about future cash flows than current cash flows, given that earnings include accruals and other adjustments reflecting a firm's long-term performance. That is, analyst earnings forecasts are inherently linked to expectations about future cash flows. Therefore, we further test the channel of cash flows by examining analyst earnings forecast biases around quarterly earnings announcements following portfolio construction. The earnings forecast biases are estimated as the difference between analyst forecasts and actual earnings scaled by the adjusted stock price at the beginning of the year. Panel B of Table 9 shows that the earnings forecast biases of the low-minus-high portfolios remain insignificant in each quarter and across all four quarters. These results collectively indicate that the channel of cash flow is not supported.

V. Robustness Tests

To mitigate concerns that the CCDS measure may suffer from look-ahead bias due to the public release of the TCFD framework in 2017 and from omitted information-quality variables, we conduct two complementary robustness tests, including the subsample analysis before and after 2017 and event studies around exogenous climate policy shocks.

A. Subsample Analysis

A potential concern with the CCDS measure is look-ahead bias, as the TCFD framework that guides our disclosure scoring measure was only publicly released in 2017. If firms during the pre-TCFD period were evaluated according to standards that were not yet observable to market participants, our results could overstate the informativeness of climate disclosures.

While such a concern is likely minimal because the TCFD codifies existing climate disclosure concepts rather than creating new ones (TCFD (2017)), and assessing TCFD-aligned terms in pre-2017 disclosures is consistent with widely accepted practices in prior studies, such as applying SASB or Loughran-McDonald dictionaries to pre-guidance periods (e.g., Loughran and McDonald (2011), Matsumura, Prakash and Vera-Muñoz (2024)), it remains important to conduct further tests to verify that our findings are robust. To address this issue, we separate the full sample into two subsamples before and after 2017 and re-estimate all baseline tests, ensuring that our results are not driven by potential look-ahead bias or temporal changes in disclosure behavior. The empirical results are reported in the Table OA10.

Panel A of Table OA10 shows that the low-minus-high portfolios sorted on CCDS show positive and statistically significant alphas both before and after June 2017, indicating that the return patterns are not solely driven by pre-TCFD periods. Panel B reports FM regressions across one-, three-, and six-month returns, where CCDS consistently exhibits negative and significant coefficients in both subsamples before and after 2017. These results demonstrate that the relationship between climate change disclosures and stock returns persists in the post-2017 sample. These results help mitigate concerns about look-ahead bias or temporal changes in disclosure practices, and provide additional support for the valuable information of CCDS priced by the market.

B. Event study

To address potential concerns about omitted variables, we implement short-window event studies around major exogenous climate policy shocks. By focusing on narrow windows surrounding these events, we minimize the influence of confounding factors and isolate the impact of climate change disclosures on stock returns.

Climate change regulations are an important climate risk factor affecting stock returns. Bolton and Kacperczyk (2023) report a higher carbon premium for carbon-intensive firms after

the Paris Agreement in 2015. Ilhan, Sautner and Vilkov (2021) document that higher carbon emissions exhibit greater volatility and tail risks associated with climate policy uncertainty. They use President Donald Trump's election as a proxy for climate shock and find that carbon tail risk reduces after the event due to a reduction in climate policy uncertainty. Hsu, Li and Tsou (2023) find that firms with higher chemical toxic emissions have positive market reactions to Trump's election as higher cumulative abnormal returns are observed. These studies suggest that firms exposed to climate risks react differently to changes in climate change actions, and specifically, a negative (positive) reaction is expected to a shift into strong (weak) environmental policy (e.g., Pástor and Veronesi (2012), Hsu, Li and Tsou (2023)). Therefore, we predict that CCDS portfolios have a strong reaction to a change in climate change policy.

To examine whether firms with climate change disclosures have different price reactions, we employ multiple events in US and Europe as climate shocks, including, *the Trump's election as 2016 President* representing a shift into weak climate policy, *the Biden's Election as 2020 President, the SEC Proposed Climate Reporting Rules, the SEC Climate Reporting Final Rules, the EU Non-Financial Reporting Directive (EU NFRD) and the EU Climate Law*, indicating a shift into strong climate policy. These events are provided in Table 10. We estimate CARs of portfolios sorted on CCDS over the time windows from one day before the event dates to three day [-1, +3] and five days [-1, +5] later[18]. Specifically, we compute the abnormal return by estimating the market model:

$$R_{i,t} = \alpha + \beta * R_{m,t} + \varepsilon_{i,t} \quad \textbf{[8]}$$

The market betas are estimated using daily data over the past one-year window ending one month before the event dates. Then in each CCDS-sorted portfolio, we compute and

[18] The results remain robust when we use longer event windows, such as [-1,+7] and [-1,+10].

average cumulative abnormal return across stocks within each portfolio using the estimated model:

$$CAR_i(T1, T2) = \sum_{T1}^{T2} AR_{i,t} = \sum_{T1}^{T2} R_{i,t} - \hat{R}_{i,t} \quad \textbf{[9]}$$

The portfolio CARs are reported in Table 10, showing an increasing pattern with CCDS in all events except for the Trump's Election. The differences in CAR between low CCDS and high CCDS portfolios are significantly positive except for the EU NFRD. This suggests that stocks with limited climate change disclosures face higher uncertainty, compared to stocks with extensive disclosures, leading to stronger negative market reactions when climate change policies become more stringent.

We also find significantly positive differences in CAR between low and high CCDS portfolios in the Trump's Election, indicating that low-disclosure firms interpret Trump's election as good news due to his claim for a more lenient environmental policy. A weak climate change policy would reduce firms' pressure for regulatory compliance and lower potential costs associated with environmental reporting and climate risk management, preserving short-term profitability. These results underscore the growing importance of climate change disclosures in shaping market behavior and investor decision-making in the context of evolving climate regulations.

VI. Conclusion

This study examines the role of climate change disclosures in capital markets using an international sample of 26 countries. Using a comprehensive vocabulary aligned with the TCFD reporting framework, we construct a measure of firm-level climate change disclosures through textual analysis of annual reports, addressing the call by Giglio, Kelly and Stroebel (2021) to leverage corporate texts for assessing climate risks. Our findings demonstrate that a

long-short trading strategy taking a long (short) position in stocks with low (high) climate change disclosures yields significant risk-adjusted returns of 0.426% and 0.649% per month in the global and US markets, respectively. These returns cannot be explained by traditional risk factors. The FM regressions specifically indicate that higher climate change disclosures are associated with lower average returns, even when controlling for firm characteristics.

The predictive ability of CCDS for stock returns operates through the cost of capital channel, as climate change disclosures are associated with higher stock liquidity, lower information uncertainty and lower implied cost of capital, lending strong support that our disclosure measure is a proxy for *transparency*. In addition, we find that climate change disclosure measure effectively captures market reactions to climate regulation shifts, and specifically, stocks with low climate change disclosures have negative (strong) price reactions to a potential shift into strong (weak) climate policy.

Our results underscore the pivotal value of climate change disclosures in shaping capital markets and improving information transparency. The growing adoption of TCFD-aligned reporting frameworks worldwide reflects investor demand for greater climate-related transparency (TCFD (2023)). This study confirms that TCFD-aligned disclosures provide decision-useful information that helps to better understand climate risks and opportunities.

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Figure 1: The Number of Listed TCFD Supporting Companies Across Countries

This figure shows the number of listed TCFD supporting companies across countries. TCFD supporter information is collected from the TCFD website (https://www.fsb-tcfd.org/). We report 26 countries with at least ten publicly listed TCFD supporting companies from 2017, the release of TCFD recommendations, till 2022. The additional details of identifying listed TCFD supporters are shown in OA I.

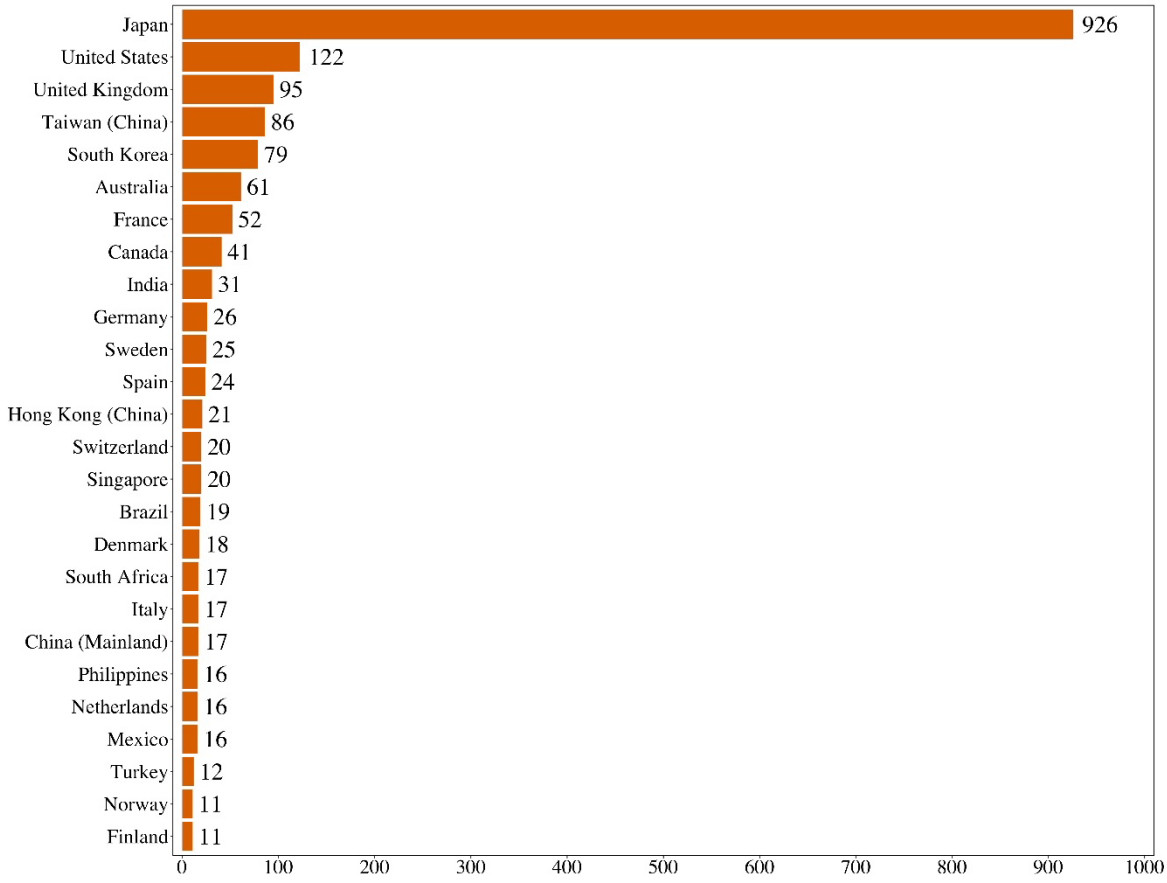
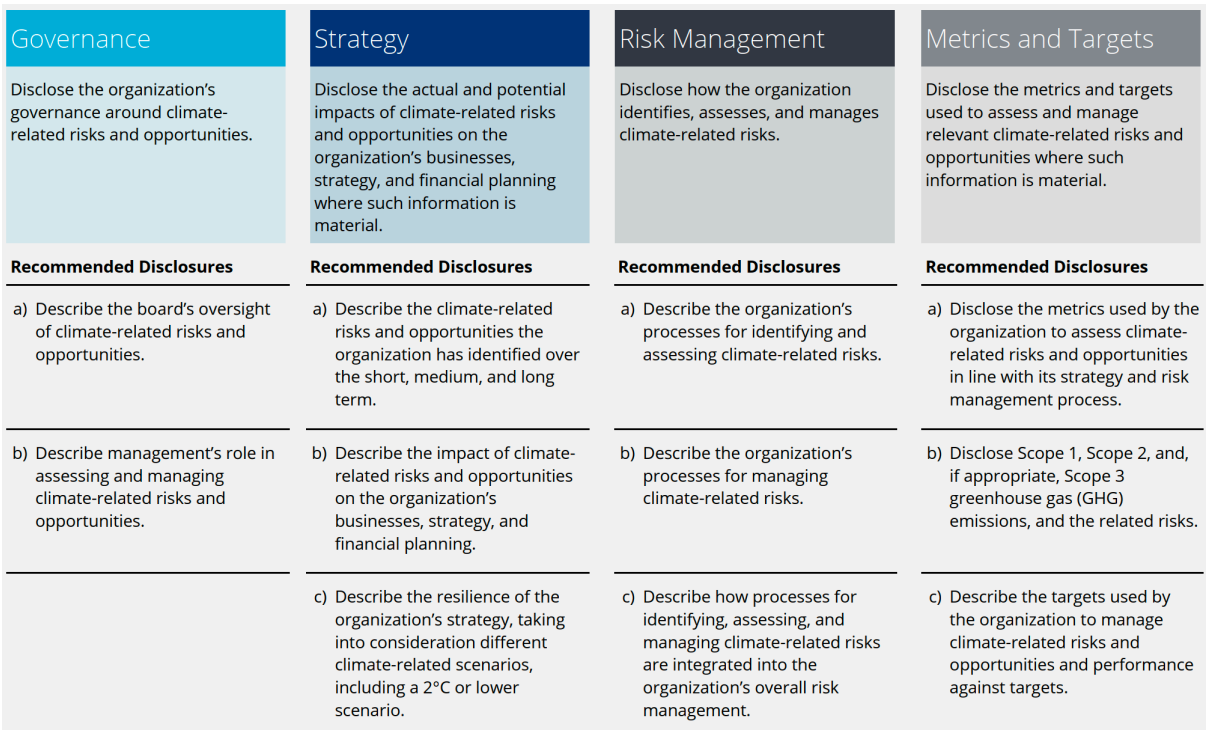


Figure 2: TCFD Recommendations for Climate Change Disclosures

This figure is a snapshot from the TCFD website (https://www.fsb-tcfd.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: Correlation Matrix

This figure shows the correlation matrix of the variables. The definition of all variables is reported in Appendix 1. The color indicates the sign of correlation coefficients for which the blue represents the negative correlation and the red represents positive correlation. The color darkness represents the strength of the correlation and the crosses represent the correlations with p-value greater than 5%.

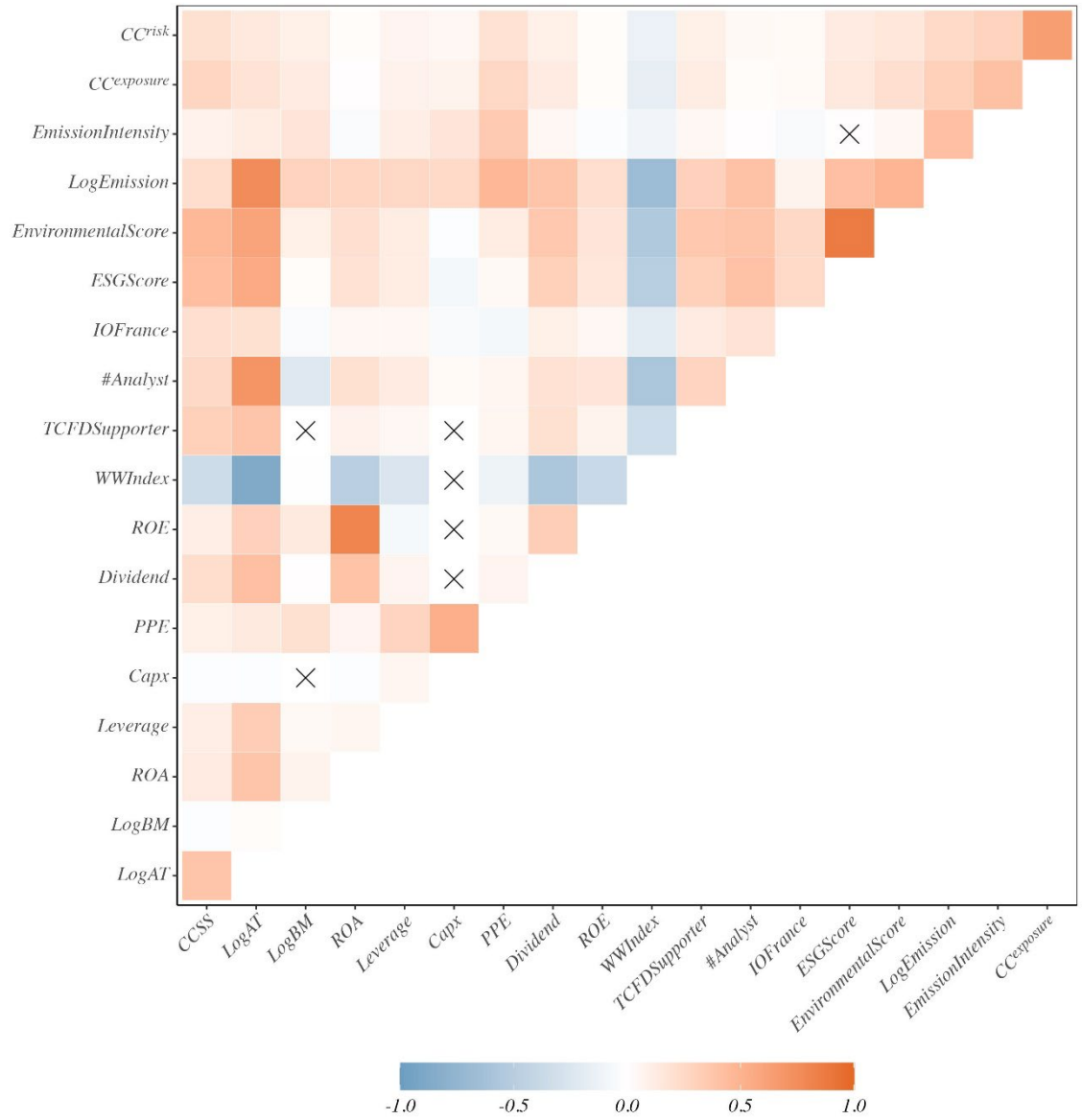


Table 1: CCDS Summary Statistics

This table shows the summary statistics of climate change disclosure scores (*CCDS*) across years in Panel A, countries in Panel B and industries in Panel C. *CCDS* is firm-level climate change disclosure calculated as the cosine similarity between a comprehensive climate change vocabulary, built upon keywords extracted from the TCFD reporting recommendations, and firms' annual reports. The measure construction details are reported in OA IV. The last two columns present the number of firm-year observations and the percentage of firms disclosing climate change information (CCDS>0).

Panel A: Climate Change Disclosure Score by Year

Fiscal Year	Mean	St.Dev	Median	Min	P25	P75	Max	Obs	Disclosure (%)
2008	0.011	0.030	0.000	0.000	0.000	0.000	0.308	11,965	15.06%
2009	0.015	0.034	0.000	0.000	0.000	0.000	0.336	11,635	21.49%
2010	0.015	0.035	0.000	0.000	0.000	0.000	0.310	11,276	22.34%
2011	0.017	0.037	0.000	0.000	0.000	0.000	0.275	11,919	24.01%
2012	0.018	0.038	0.000	0.000	0.000	0.000	0.289	11,825	24.61%
2013	0.020	0.042	0.000	0.000	0.000	0.026	0.297	12,005	25.97%
2014	0.022	0.043	0.000	0.000	0.000	0.031	0.316	12,224	26.87%
2015	0.023	0.046	0.000	0.000	0.000	0.035	0.320	12,450	27.82%
2016	0.028	0.050	0.000	0.000	0.000	0.050	0.469	12,353	33.79%
2017	0.034	0.056	0.000	0.000	0.000	0.061	0.464	12,621	36.50%
2018	0.039	0.064	0.000	0.000	0.000	0.068	0.480	13,032	38.11%
2019	0.054	0.077	0.000	0.000	0.000	0.085	0.485	12,782	46.89%
2020	0.066	0.088	0.033	0.000	0.000	0.102	0.522	12,994	51.82%
2021	0.085	0.099	0.062	0.000	0.000	0.133	0.487	13,143	61.27%
2022	0.098	0.101	0.074	0.000	0.000	0.162	0.482	12,691	67.12%

Panel B: Climate Change Disclosure Score by Country

Country	Mean	Std.Dev	Median	Min	P25	P75	Max	Obs	Disclosure (%)
Australia	0.017	0.048	0.000	0.000	0.000	0.000	0.480	23,797	21.57%
Brazil	0.037	0.073	0.000	0.000	0.000	0.049	0.409	1,255	32.51%
Canada	0.037	0.061	0.000	0.000	0.000	0.060	0.391	4,458	38.85%
China	0.030	0.047	0.000	0.000	0.000	0.054	0.261	1,192	37.75%
Denmark	0.038	0.072	0.000	0.000	0.000	0.050	0.407	1,326	32.58%
Finland	0.067	0.088	0.000	0.000	0.000	0.115	0.402	1,655	49.91%
France	0.113	0.108	0.097	0.000	0.000	0.185	0.474	3,689	68.28%
Germany	0.045	0.068	0.000	0.000	0.000	0.077	0.411	4,409	41.94%
Hong Kong	0.042	0.063	0.000	0.000	0.000	0.080	0.413	15,787	39.35%
India	0.027	0.052	0.000	0.000	0.000	0.044	0.522	24,876	31.71%
Italy	0.050	0.080	0.000	0.000	0.000	0.082	0.421	2,238	40.53%
Japan	0.099	0.099	0.073	0.000	0.000	0.186	0.439	4,093	63.40%
Mexico	0.064	0.086	0.032	0.000	0.000	0.100	0.384	342	56.73%
Netherlands	0.088	0.096	0.062	0.000	0.000	0.147	0.431	1,072	62.97%
Norway	0.062	0.097	0.000	0.000	0.000	0.100	0.490	1,967	42.76%
Philippines	0.055	0.093	0.000	0.000	0.000	0.082	0.399	2,610	34.25%
Singapore	0.020	0.052	0.000	0.000	0.000	0.000	0.395	4,768	20.24%
South Africa	0.058	0.075	0.000	0.000	0.000	0.100	0.405	3,640	49.78%
South Korea	0.057	0.082	0.021	0.000	0.000	0.083	0.442	756	51.32%
Spain	0.107	0.107	0.085	0.000	0.000	0.181	0.474	956	68.31%
Sweden	0.061	0.086	0.000	0.000	0.000	0.106	0.449	3,706	46.76%
Switzerland	0.042	0.077	0.000	0.000	0.000	0.064	0.487	2,424	36.06%
Taiwan	0.074	0.084	0.051	0.000	0.000	0.127	0.385	2,027	57.62%
Turkey	0.045	0.074	0.000	0.000	0.000	0.076	0.427	1,487	36.58%
United Kingdom	0.057	0.095	0.000	0.000	0.000	0.090	0.511	18,903	38.88%
United States	0.022	0.034	0.000	0.000	0.000	0.055	0.252	51,482	31.98%

Panel C: Climate Change Disclosure Score by Industry

Industry	Mean	Std.Dev	Median	Min	P25	P75	Max	Obs	Disclosure (%)
Basic Materials	0.032	0.061	0.000	0.000	0.000	0.046	0.468	23,702	33.70%
Consumer Discretionary	0.036	0.066	0.000	0.000	0.000	0.057	0.483	30,578	34.70%
Consumer Staples	0.048	0.071	0.000	0.000	0.000	0.072	0.490	10,059	46.30%
Energy	0.050	0.067	0.031	0.000	0.000	0.077	0.489	9,838	52.40%
Financials	0.037	0.073	0.000	0.000	0.000	0.054	0.511	24,690	30.80%
Health Care	0.017	0.046	0.000	0.000	0.000	0.000	0.440	18,419	17.70%
Industrials	0.045	0.072	0.000	0.000	0.000	0.070	0.482	35,569	41.40%
Real Estate	0.051	0.078	0.000	0.000	0.000	0.070	0.474	3,751	47.30%
Technology	0.026	0.057	0.000	0.000	0.000	0.027	0.522	18,229	25.60%
Telecommunications	0.036	0.068	0.000	0.000	0.000	0.054	0.442	5,191	32.30%
Utilities	0.078	0.078	0.071	0.000	0.000	0.111	0.447	4,889	68.80%

Table 2: Sample Construction

The table reports sample formation over the period between fiscal year 2008 and 2022. The sample is initially constructed from sample firms with climate change disclosure scores. Next, we merge the sample with various databases and then drop financial firms with SIC codes between 6000 and 6999, as well as firms with negative book equity values or total assets for a year.

Data Filters	Firm-Year Observation	# of Unique Firms
Sample with climate change disclosure score available between fiscal year 2008 and 2022	184,915	19,853
Sample after merging with WorldScope, Datastream, Compustat, CRSP, I/B/E/S, Factset and LSEG ESG databases	166,730	18,522
Sample after deleting the financial firms with SIC between 6000 and 6999	140,736	15,769
Sample after deleting firm-year observations with negative book equity value or total assets	126,727	14,994

Table 3: Descriptive Statistics

This table reports the summary statistics of variables for the full sample. *LogAT* is the natural logarithm of total assets in US dollars. *LogBM* is the natural logarithm of book value of equity divided by the market value of equity. *ROA* is the return on asset, calculated by the net income before extraordinary items divided by total assets. *Leverage* is a firm leverage ratio, measured by the total debts divided by the total assets. *Capx* is the capital expenditure scaled by total assets. *PPE* is the property, plant and equipment scaled by total assets. *Dividend* is an indicator variable that equals one if the firm has a common dividend payment, and zero otherwise. *ROE* is the return on equity, calculated by the net income before extraordinary items divided by book equity. *WWIndex* is financial constraint index. *TCFDSupporter* is a dummy variable that equals one if the firm is a TCFD supporter and zero otherwise. *#Analyst* is the analyst following, measured by the natural logarithm of the number of analysts covering the firm. *IOFrance* is the firm's ownership held by French institutional investors. *ESGScore* and *EnvironmentalScore* are the ESG and Environmental scores from the LSEG ESG database, respectively. *LogEmission* is the natural logarithm of total Scope 1, 2 and 3 emissions. *EmissionIntensity* is total Scope 1, 2, and 3 emissions divided by a firm's revenue in US dollars. CC^{risk} is climate change risk measure, calculated by the frequency of bigrams related to climate change together with the words "risk" or "uncertainty" in the earnings conference call. $CC^{exposure}$ is climate change exposure measure, calculated by the frequency of bigrams related to climate change in the earnings conference call. The sample period spans between fiscal year 2008 and 2022. All variables are winsorized by the 1st and 99th percentile.

Variables	Observation	Mean	Std.Dev	P25	Median	P75
CCDS	126,727	0.042	0.069	0.000	0.000	0.067
LogAT	126,727	19.685	2.297	18.043	19.588	21.309
LogBM	126,727	-0.535	1.015	-1.155	-0.486	0.135
ROA	126,727	-0.022	0.214	-0.027	0.030	0.071
Leverage	126,560	0.208	0.182	0.036	0.181	0.332
Capx	124,349	0.047	0.058	0.011	0.028	0.059
PPE	126,700	0.267	0.236	0.072	0.199	0.409
Dividend	126,727	0.537	0.499	0.000	1.000	1.000
ROE	126,727	-0.074	0.593	-0.056	0.065	0.142
WWIndex	119,542	-0.903	0.136	-0.996	-0.910	-0.822
TCFDSupporter	126,727	0.072	0.258	0.000	0.000	0.000
#Analysts	86,443	1.499	1.051	0.693	1.609	2.398
IOFrance	99,611	0.004	0.011	0.000	0.000	0.002
ESGScore	45,044	0.450	0.204	0.284	0.437	0.611
EnvironmentalScore	45,028	0.370	0.286	0.091	0.353	0.613
LogEmission	46,336	11.324	2.843	9.481	11.368	13.214
EmissionIntensity ($x10^4$)	46,336	0.033	0.092	0.001	0.004	0.017
$CC^{exposure}$	42,007	0.141	0.276	0.015	0.041	0.123
CC^{risk}	42,007	0.005	0.014	0.000	0.000	0.000

Table 4: Firm Characteristics across Portfolios

This table reports the summary statistics of the portfolios sorted on climate change disclosures (CCDS) for the global sample in Panel A, the US sample in Panel B, and the global excluding the US sample in Panel C. In each year, we sort sample stocks into three groups based on climate change disclosure scores using the most recent data. The sample stocks with zero CCDS are classified into one group. We then calculate the means of several variables for the portfolio firms and estimate the difference in means between high CCDS portfolios and low CCDS portfolios. All the variables are defined on Appendix I.

	Zero	Low	Median	High	High-Low	
					difference	*p-value*
Panel A: Global Sample						
LogAT	18.79	19.94	20.82	21.60	1.66	0.000
LogBM	-0.55	-0.61	-0.60	-0.58	0.04	0.002
ROA	-0.08	-0.02	0.01	0.03	0.06	0.000
Leverage	0.17	0.22	0.24	0.24	0.02	0.000
Capx	0.05	0.06	0.05	0.04	-0.01	0.000
PPE	0.24	0.31	0.33	0.30	-0.01	0.000
Dividend	0.42	0.54	0.65	0.79	0.25	0.000
ROE	-0.17	-0.06	0.01	0.06	0.12	0.000
WWIndex	-0.86	-0.92	-0.96	-1.01	-0.09	0.000
Panel B: US Sample						
LogAT	19.79	21.00	21.48	22.38	1.39	0.000
LogBM	-0.95	-0.76	-0.88	-0.62	0.13	0.000
ROA	-0.09	0.00	0.00	0.02	0.02	0.000
Leverage	0.18	0.28	0.28	0.29	0.02	0.000
Capx	0.03	0.06	0.05	0.06	0.00	0.024
PPE	0.16	0.32	0.32	0.47	0.15	0.000
Dividend	0.30	0.45	0.54	0.72	0.26	0.000
ROE	-0.21	-0.02	-0.01	0.03	0.06	0.000
WWIndex	-0.89	-0.96	-0.99	-1.04	-0.08	0.000
Panel C: Global ex US Sample						
LogAT	18.40	19.47	20.57	21.93	2.46	0.000
LogBM	-0.40	-0.52	-0.52	-0.60	-0.08	0.000
ROA	-0.07	-0.02	0.02	0.04	0.06	0.000
Leverage	0.17	0.20	0.23	0.24	0.05	0.000
Capx	0.06	0.05	0.04	0.04	-0.01	0.000
PPE	0.27	0.32	0.29	0.30	-0.02	0.000
Dividend	0.47	0.59	0.68	0.82	0.23	0.000
ROE	-0.16	-0.06	0.02	0.08	0.13	0.000
WWIndex	-0.85	-0.90	-0.96	-1.02	-0.12	0.000

Table 5: Sorting Portfolio Returns

This table shows the average excess returns of portfolios sorted on climate change disclosure scores for the Global sample (Panel A), the US sample (Panel B) and Global ex US sample (Panel C). In each year, we sort sample stocks into three groups based on climate change disclosure scores (CCDS) using the most recent data. The sample stocks with zero CCDS are classified into one group. The low-minus-high columns represent the portfolios that take a long (short) position in the percentile of the portfolio with the lowest (highest) climate change disclosure scores. The zero-minus-high columns represent the portfolios that take a long (short) position in the percentile of the portfolio with the zero (highest) climate change disclosure scores. *# of Stocks* represents the average number of stocks in the portfolio. We present an average monthly excess return over a risk-free rate, t-statistics in each sample. The portfolio returns are value-weighted by firms' market capitalization. The sample period spans from July 2009 to December 2023.

	Zero	Low	Median	High	Low-High	Zero-High
Panel A: Global Sample						
Excess return (%)	1.661	1.767	1.369	1.203	0.564	0.458
t-statistic	(5.32)	(5.52)	(4.73)	(4.60)	(3.39)	(2.87)
# of Stocks	5,156	1,217	1,189	700	1,917	5,856
Panel B: US Sample						
Excess return (%)	1.732	2.012	1.590	1.176	0.836	0.557
t-statistic	(5.02)	(5.28)	(4.87)	(3.75)	(4.08)	(2.92)
# of Stocks	1,448	317	310	184	501	1,632
Panel C: Global ex US Sample						
Excess return (%)	1.525	1.393	1.244	1.187	0.206	0.338
t-statistic	(5.71)	(5.56)	(4.86)	(4.36)	(1.80)	(2.35)
# of Stocks	3,679	987	853	442	1,429	4,120

Table 6: Time-series Factor Pricing Test

This table shows the time-series regressions of monthly returns of CCDS-sorted portfolios on the Fama-French five factors for the Global sample (Panel A), the US sample (Panel B) and the Global ex US sample (Panel C). The Low-High column represents the portfolios that take a long (short) position in the percentile of portfolios with lowest (highest) values. The Zero-High column represents the portfolios that take a long (short) position in the percentile of portfolios with zero (highest) CCDS values. The risk-adjusted returns are reported in percentage and the factor loadings are omitted in the table. The t-statistics in parentheses are calculated based on the standard errors corrected by the Newey-West with 12 lags. The samples span over a period between July 2009 and December 2023. *, **, *** indicate the 10%, 5% and 1% significance level, respectively.

	Zero	Low	Median	High	Low-High	Zero-High
Observations	174	174	174	174	174	174
Panel A: Global Sample						
α	0.927***	0.932***	0.512***	0.506***	0.426***	0.421***
	(12.67)	(7.79)	(6.85)	(5.78)	(3.78)	(4.34)
Adj-R2	0.94	0.88	0.94	0.83	0.28	0.37
Panel B: US Sample						
α	0.606***	0.768***	0.426***	0.119	0.649***	0.487***
	(8.76)	(4.77)	(6.38)	(1.02)	(3.71)	(3.40)
Adj-R2	0.96	0.88	0.93	0.88	0.35	0.43
Panel C: Global ex US Sample						
α	0.498**	0.369**	0.17	0.094	0.275***	0.404***
	(2.43)	(2.08)	(1.18)	(0.79)	(2.64)	(3.04)
Adj-R2	0.56	0.58	0.66	0.65	0.10	0.08

Table 7: Fama-Macbeth Cross-sectional Test

This table presents the results of monthly FM regressions of individual stock monthly excess returns on climate change disclosure (CCDS) and firm characteristics. The firm characteristics are market capitalization and book-to-market ratio, past twelve-month return, return volatility, investment, profitability, leverage ratio, property plant and equipment, and financial constraints. *LogME* is the natural logarithm of market capitalization. *LogBM* is the natural logarithm of the most recent available book value divided by the market capitalization. *Investment* is computed as total asset growth from fiscal year t-2 to fiscal year t-1. *ROE* is measured as income before extraordinary items divided by shareholders' equity. *Leverage* is defined as the firm's book leverage ratio. *PPE* is calculated as PPE scaled by total assets. *RetPrior12M* is the average stock return over the past year. *RetVolPrior12M* is the standard deviation of the stock return over the past year. At each firm-month level, the dependent variable is the average monthly return over the subsequent one and twelve months, respectively. All independent variables are winsorised at 1% and 99% level and standardized with zero mean and one-unit standard deviation. In each month, we conduct the cross-sectional regressions of monthly returns on CCDS and firm characteristics. The average coefficients from monthly regressions are reported and the t-statistics in parenthesis are calculated as average coefficients divided by the Newey-West standard errors with 12 lags. The observations are the average number of individual stocks in monthly cross-sectional regressions. The sample period is between July 2009 and December 2023.

	Global Sample		US Sample		Global ex US Sample	
	RET_1M	RET_12M	RET_1M	RET_12M	RET_1M	RET_12M
CCDS	-0.109***	-0.115***	-0.132**	-0.141***	-0.071**	-0.084***
	(-3.55)	(-8.91)	(-2.42)	(-5.73)	(-2.02)	(-5.29)
LogME	-0.211*	-0.239***	-0.047	-0.127**	-0.334***	-0.337***
	(-1.69)	(-4.46)	(-0.42)	(-2.54)	(-2.58)	(-6.15)
LogBM	-0.006	0.007	0.152	0.144***	-0.046	-0.027
	(-0.14)	(0.37)	(1.63)	(3.79)	(-0.92)	(-1.23)
ROE	0.180***	0.195***	0.185**	0.187***	0.168***	0.195***
	(4.30)	(10.95)	(2.23)	(5.58)	(3.85)	(10.50)
Investment	-0.200***	-0.186***	-0.103**	-0.089***	-0.213***	-0.199***
	(-6.43)	(-11.45)	(-2.01)	(-3.99)	(-5.99)	(-12.58)
RetPrior12M	0.311***	0.276***	0.047	0.102***	0.389***	0.314***
	(4.04)	(9.24)	(0.52)	(2.81)	(5.39)	(10.39)
RetVolPrior12M	-0.108	-0.124***	0.073	0.014	-0.202**	-0.207***
	(-1.10)	(-3.01)	(0.50)	(0.25)	(-2.13)	(-5.09)
PPE	0.009	0.002	-0.097	-0.080**	0.036	0.016
	(0.13)	(0.06)	(-1.07)	(-2.15)	(0.51)	(0.54)
Leverage	0.033	0.03	0.176***	0.130***	-0.03	-0.01
	(0.72)	(1.60)	(2.94)	(5.22)	(-0.58)	(-0.47)
WWIndex	-0.280***	-0.341***	-0.169	-0.276***	-0.347***	-0.389***
	(-2.70)	(-7.95)	(-1.40)	(-5.98)	(-2.93)	(-8.49)
Observations	2987	2813	740	686	2248	2127

Table 8: The Channel of Cost of Equity

This table shows the regression results of the effects of firm-level climate change disclosure on the information environment for the full sample. *Bid-Ask Spread*, *Amihud's Illiquidity (AIM)* and *the number of zero return (ZeroRet)*. *Bid-Ask Spread* is the natural logarithm of the median value of the difference between daily closing bid and ask prices divided by the midpoint in a year. *Amihud's Illiquidity* is calculated as the natural logarithm of the median value of the daily absolute stock returns divided by daily dollar trading volumes in US millions over a year. *ZeroRet* is the number of trading days with zero returns scaled by the potential trading days over a year. *ImpliedCOE* is calculated as the average value of four measures: Easton's PEG model (2004), Gebhardt et al. (2001), Claus and Thomas (2001) and Ohlson and Juettner-Nauroth (2005)'s model. *RetVol* as the standard deviation of daily stock return over a one-year window. *FError* is measured as the average value of the absolute difference between analyst mean estimates and actual earnings, then scaled by stock price at the beginning of the year. The *t-statistics* in parentheses are adjusted by the clustered standard error at the firm level. *, **, *** represent the 10%, 5% and 1% significance level, respectively.

	Liquidity			Uncertainty			COE
	Bid-ask Spread	AIM	ZeroRet	RetVol	FError(0)	FError(1)	ImpliedCOE
CCSS	-0.028***	-0.013***	-0.010**	-0.023***	-0.040**	-0.051***	-1.091**
	(-8.20)	(-5.45)	(-2.46)	(-5.61)	(-2.19)	(-2.81)	(-2.26)
LogAT	-0.344***	-0.496***	-0.307***	-0.146***	-1.312***	-1.480***	-27.068***
	(-22.34)	(-42.27)	(-15.30)	(-7.02)	(-15.14)	(-16.68)	(-8.00)
LogBM	0.184***	0.223***	0.168***	0.174***	1.420***	1.263***	11.473***
	(47.17)	(64.25)	(26.87)	(27.62)	(49.69)	(46.84)	(11.68)
ROA	-0.046***	-0.036***	-0.047***	-0.107***	-0.377***	-0.210***	-7.055***
	(-14.51)	(-13.19)	(-8.95)	(-19.90)	(-15.15)	(-8.64)	(-5.94)
Capx	-0.013***	-0.003	-0.024***	-0.003	-0.011	-0.023	-1.421**
	(-4.62)	(-1.34)	(-5.31)	(-0.58)	(-0.47)	(-1.02)	(-2.08)
PPE	0.023***	0.021***	-0.004	0.012	0.149***	0.088*	0.103
	(2.99)	(3.31)	(-0.30)	(1.04)	(2.91)	(1.67)	(0.07)
Leverage	0.085***	0.105***	0.059***	0.136***	0.638***	0.485***	8.032***
	(19.07)	(29.06)	(10.06)	(21.46)	(23.41)	(18.58)	(7.38)
WWIndex	0.011***	0.004	0.015***	-0.007*	0.005	0.002	1.733
	(3.66)	(1.46)	(2.74)	(-1.80)	(0.18)	(0.08)	(1.22)
#Analyst	-0.046***	-0.066***	-0.051***	-0.009	-0.148***	-0.126***	-0.945
	(-9.61)	(-15.66)	(-7.52)	(-1.36)	(-4.61)	(-4.05)	(-1.04)
RetVolPrior12M	-0.020***	-0.027***	-0.033***	0.068***	0.043**	-0.019	6.731***
	(-8.95)	(-14.07)	(-9.76)	(18.15)	(2.37)	(-1.11)	(10.77)
Adjusted R2	0.91	0.94	0.82	0.74	0.55	0.52	0.58
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74,161	74,161	74,161	77,634	69,099	60,153	62,300

Table 9: Earnings Announcement

The table shows the cumulative abnormal returns (Panel A) and analyst earnings forecast errors (Panel B) around the quarterly earnings announcement of stocks following the CCDS-sorted portfolio constructions in each June. Quarterly earnings announcement dates and analyst earnings forecasts are obtained from the Compustat and IBES databases. In Panel A, the daily abnormal return is estimated using the market model in which the market betas are calculated with daily data over the past one-year window ending one month before the event dates. In Panel B, the earnings forecast biases are calculated as the average of the difference between actual earnings and analyst forecasts expressed in US dollars, divided by the adjusted stock price in US dollars at the beginning of the year.

Panel A: CARs around Earnings Announcement Following Portfolio Construction

Event Window	Low	Median	High	Low-High	*t-statistic*	*p-value*
[-1, 3]	0.0016	0.0013	0.0010	0.0006	0.563	0.574
[-1, 5]	0.0012	0.0013	0.0006	0.0005	0.474	0.636

Panel B: Earnings Forecast Biases Following Portfolio Construction

Quarters	Low	Median	High	Low-High	*t-statistic*	*p-value*
1	0.0006	0.0003	0.0001	0.0005	1.677	0.094
2	0.0004	0.0001	-0.0001	0.0005	1.743	0.081
3	-0.0002	0.0001	-0.0001	-0.0002	-0.533	0.594
4	0.0005	0.0008	0.0007	-0.0001	-0.441	0.659
All	0.0003	0.0003	0.0001	0.0002	1.362	0.173

Table 10: Event Study in the US and Europe

This table summarises the average cumulative abnormal returns of stocks in three CCDS-sorted portfolios over the event windows [-1, +3] and [-1, +5]. The last column reports the *t-statistics* of the low-minus-high portfolios' CARs. We estimate the abnormal return using the market model in which the market betas are calculated with daily data over the past one-year window ending one month before the event dates. Then, the CARs across stocks in each portfolio are computed and averaged over the event windows.

CAR	Event Window	Low	Median	High	Low-High	*t-statistic*	*p-value*
Panel A: Trump Selection							
2016-11-08	[-1, 3]	0.0285	0.0130	-0.0063	0.0348	3.983	0.000
2016-11-08	[-1, 5]	0.0381	0.0220	0.0034	0.0347	4.157	0.000
Panel B: Biden Election							
2020-11-24	[-1, 3]	-0.0013	0.0064	0.0100	-0.0113	-1.796	0.073
2020-11-24	[-1, 5]	0.0028	0.0114	0.0187	-0.0158	-1.966	0.050
Panel C: SEC Proposed Climate Reporting Rules							
2022-03-21	[-1, 3]	-0.0223	-0.0186	-0.0018	-0.0206	-3.688	0.000
2022-03-21	[-1, 5]	-0.0320	-0.0310	-0.0078	-0.0242	-3.575	0.000
Panel D: SEC Climate Reporting Final Rules							
2024-03-06	[-1, 3]	0.0052	0.0102	0.0182	-0.0130	-2.730	0.006
2024-03-06	[-1, 5]	-0.0027	0.0018	0.0121	-0.0148	-2.571	0.010
Panel E: EU Non-Financial Reporting Directive							
2014-04-15	[-1, 3]	-0.0042	-0.0053	0.0003	-0.0045	-1.206	0.229
2014-04-15	[-1, 5]	-0.0037	-0.0020	0.0023	-0.0061	-1.278	0.203
Panel F: EU Climate Law							
2020-03-04	[-1, 3]	-0.0508	-0.0365	-0.0274	-0.0234	-3.648	0.000
2020-03-04	[-1, 5]	-0.0524	-0.0274	-0.0127	-0.0396	-4.585	0.000

Appendix I: Variables Definition

Variables	Description	Data Source
CCDS	Climate Change Similarity Score, a measure of climate change disclosure through textual analysis of annual reports	LSEG Workspace & EDGAR, Self-constructed
LogAT	The natural logarithm of a firm's total asset in US dollar in the year	Compustat
LogBM	The natural logarithm of a firm's book value of the equity to market value ratio in the year	Compustat
ROA	The return on asset, measured by income before extraordinary item divided by total asset	Compustat
Leverage	The total debt divided by total asset where total debt is equal to debt in current liabilities plus long-term debt	Compustat
Capx	The capital expenditure, scaled by total asset	Compustat
PPE	The property, plant and equipment, scaled by total asset	Compustat
Dividend	An indicator variable that equals one if the firm has a common dividend payment, and zero otherwise	Compustat
ROE	The return on equity, calculated by the net income before extraordinary items divided by book equity	Compustat
Investment	The growth rate in total asset	Compustat
WWIndex	Financial constraint index developed by Whited and Wu (2006)	Compustat
TCFDSupporter	An indicator variable equal to 1 if the firm is a TCFD Supporter, and otherwise 0. See the details: https://www.fsb-tcfd.org/support-tcfd/	TCFD Website
#Analysts	The analyst following, measured by the natural logarithm of the number of analysts covering the firm	I/B/E/S
IOFrance	The percentage ownership held by French institutional investors	Factset
ESGScore	The ESG scores from the LSEG ESG database	LSEG ESG
EnvironmentalScore	The Environmental scores from the LSEG ESG database	LSEG ESG
LogEmission	The natural logarithm of total Scope 1, 2 and 3 emissions from LSEG ESG database	LSEG ESG
EmissionIntensity	Total Scope 1, 2 and 3 emissions scaled by firm's revenue in US dollar	LSEG ESG
FError(0/1)	A firm's analyst forecast error at year t for current year, one year ahead. The analyst forecast error is measured as the average value of the absolute difference between analyst mean estimates and actual earnings using I/B/E/S summary file, then scaled by stock price at the beginning of the year	I/B/E/S
RetPrior12M	The average monthly stock return over the past one year	Compustat/CRSP
RetVolPrior12M	The standard deviation of the monthly stock return over the past one year	Compustat/CRSP
ImpliedCOE	The average value of four measures: Easton's PEG model (2004), Gebhardt et al. (2001), Claus and Thomas (2001), and Ohlson and Juettner-Nauroth (2005)'s model	I/B/E/S

Bid-ask Spread	The natural logarithm of the median value of the difference between daily closing bid and ask prices divided by the midpoint in a year	Datastream
AIM	Amihud's Illiquidity, computed as the natural logarithm of the median value of the daily absolute stock returns divided by daily dollar trading volumes in US millions over a year	Datastream
ZeroRet	The number of trading days with zero returns scaled by the potential trading days over a year	Datastream
CC^{risk}	Climate change risk measure, calculated by the frequency of bigrams related to climate change together with the words "risk" or "uncertainty" in the earnings conference call	Sautner et.al (2023)
$CC^{exposure}$	Climate change exposure measure, calculated by the frequency of bigrams related to climate change in the earnings conference call	Sautner et.al (2023)

Online Appendix

For

Climate Risk Disclosures:

Risk Exposure or Enhanced Transparency

OA I: Listed TCFD Supporting Firms Sample

Step1. We obtain an initial sample of organizations that become TCFD supporters as of June 2023 after the launch of the TCFD recommendation in June 2017 from the TCFD website (https://www.fsb-tcfd.org/supporters/).

Step2. We delete organizations that are not companies from some industries, named *"Academia, Education, and/or Research", "Accounting Firm", "Asset Management/Investment Management", "Credit Rating Agency", "Foundation or Endowment", "Other Government", "Government Ministry", "Index", "Industry/Professional Association", "Local Government", "National Government", "NGO/Nonprofit", "Pension", "Private Equity", "Proxy Firm", "Public Finance Organization", "Public Sector Association", "Reporting Standards & Frameworks", "Sovereign Wealth Fund", "Supervisors and Regulators"*.

Step3. To perform a good matching with our database, we cleanse TCFD supporter names by converting their name to lower case and removing accents and punctuations. In addition, we do some transformation of company names suffix, for example, "corporation" to "corp", "limited" to "ltd", "incorporated" to "inc".

Step4. We further perform manual matching for unmatched names and double check for matched company names via industry and county information that TCFD provides. Finally, there is an international sample of 2145 listed TCFD supporting firms with ISINs available from 60 countries and regions.

OA II: Construction of Country and Firm Samples

Step1. Identifying Country Sample

Our sample spans the period from fiscal year 2008 to 2022. We utilize an international sample of 26 countries for which we require at least ten TCFD supporting firms as of the end of 2022. These 26 countries are Australia, Brazil, Canada, China (Mainland), Denmark, Finland, France, Germany, Hong Kong (China), India, Italy, Japan, Mexico, Netherlands, Norway, Philippines, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan (China), Turkey, United Kingdom, and United States.

Step2. Selecting Constituent Lists in Each Country

Refinitiv Datastream and WorldScope provide different constituent lists for each country. To minimize survivorship bias, we combine all active and dead stocks in each country from constituent lists provided by Datastream and WorldScope and remove the duplicates.

Table OA1: Constituent List

Country	Constituent List Code
Australia	WSCOPEAU,DEADAU,FAUALL
Brazil	WSCOPEBR,DEADBR,FBRALL
Canada	WSCOPECN,DEADCA1,DEADCA2,DEADCA3,DEADCA4, DEADCA5,DEADCA6,FCAALL
China (Mainland)	WSCOPECH,DEADCN,FCNALL
Denmark	WSCOPEDK,DEADDK,FDKALL
Finland	WSCOPEFN,DEADFI,FFIALL
France	WSCOPEFR,DEADFR,FFRALL
Germany	WSCOPEBD,DEADDE1,DEADDE2,DEADDE3,DEADDE4, DEADDE5,DEADDE6,DEADDE7,DEADDE8,DEADDE9,FD EALL1,FDEALL2,FDEALL3,FDEALL4,FDEALL5,FDEALL 6,FDEALL7,FDEALL8
Hong Kong (China)	WSCOPEHK,DEADHK,FHKALL
India	WSCOPEIN,DEADIN,FINALL
Italy	WSCOPEIT,FITALL,DEADIT
Japan	WSCOPEJP,DEADJP,FJPALL
Mexico	WSCOPEMX,DEADMX,FMXALL
Netherlands	WSCOPENL,DEADNL,FNLALL
Norway	WSCOPENW,DEADNO,FNOALL
Philippines	WSCOPEPH,DEADPH,FPHALL
Singapore	WSCOPESG,DEADSG,FSGALL
South Africa	WSCOPESA,DEADZA,FZAALL

South Korea	WSCOPEKO,DEADKR,FKRALL
Spain	WSCOPEES,FESALL,DEADES
Sweden	WSCOPESD,DEADSE,FSEALL
Switzerland	WSCOPESW,FCHALL,DEADCH
Taiwan (China)	WSCOPETA,DEADTW,FTWALL
Turkey	WSCOPETK,DEADTR,FTRALL
United Kingdom	WSCOPEUK,DEADGB,FGBALL
United States	FUSAA,FUSAB,FUSAC,FUSAD,FUSAE,FUSAF,FUSAG,DEADUS1,DEADUS2,DEADUS3,DEADUS4,DEADUS5,DEADUS6,DEADUS7,DEADUS8,DEADUS9,DEADUS10,DEADUS11,DEADUS12

Step3. Screening Firm Sample

Following Krueger, Sautner, Tang and Zhong (2024), we construct the sample firms by the steps below.

Table OA2: Sample Firm Construction

Step	Items Involved	Screening Procedures
0		All active and dead securities from 26 countries
1	TYPE = 'EQ'	Keep the security whose instrument type is equity
2	MAJOR = 'Y'	Keep the primary security within a company. Only one security can be assigned MAJOR, usually the initial security or largest by market capitalisation.
3	ISINID ='P'	Keep the primary ISIN within a security with multiple ISINs
4	ADP =1	Keep securities whose stock price is adjusted for corporate actions, such as stock splits and right issues
5	TRAD	Delete stocks whose equity is not ordinary share, such as ADR, Closed-End Fund, Debenture, Note, etc.
6	EXMNEM	Keep the stocks that are traded on the major domestic exchange. (See Table OA3 below)
7	GEOGN == GEOLN	Require the home country of a firm same as its listing country
8	ENAME	Delete the security whose extended names contain suspicious words, indicating non-common equity, such as preferred shares/units (Campbell, Cowan and Salotti, 2010; Landis and Skouras, 2021)
9	INDG	Delete industry codes for investment vehicles (Griffin, Kelly and Nardari, 2010)

Table OA3: The Primary Exchanges in Each Country

Countries	Country Code	Primary Stock Exchanges	Exchange Code
Australia	AU	Australian Stock Exchange	ASX
Brazil	BR	B3 Brasil Bolsa	BSP
Canada	CA	Toronto Stock Exchange	TSE
China (Mainland)	CN	Shenzhen Stock Exchange; Shanghai Stock Exchange	SHE, SHG
Denmark	DK	Copenhagen Stock Exchange	CSE
Finland	FI	Helsinki Stock Exchange	HEL
France	FR	Paris Stock Exchange	PAR
Germany	DE	Frankfurt Stock Exchange	FRA
Hong Kong (China)	HK	Hong Kong Stock Exchange	HKG
India	IN	National India Stock Exchange	NSE
Italy	IT	Milan Stock Exchange	MIL
Japan	JP	Tokyo Stock Exchange; Osaka Stock Exchange	TKS, OSE
Mexico	MX	Mexico Stock Exchange	MEX
Netherlands	NL	Amsterdam Stock Exchange	AMS
Norway	NO	Oslo Stock Exchange	OSL
Philippines	PH	Philippine Stock Exchange	PHS
Singapore	SG	Stock Exchange of Singapore	SES
South Africa	ZA	Johannesburg Stock Exchange	JSE
South Korea	KR	Korea Exchange	KRX
Spain	ES	Madrid Stock Exchange	MAD
Sweden	SE	Stockholm Stock Exchange	OME
Switzerland	CH	Six Swiss Exchange	SWX
Taiwan (China)	TW	Taiwan Stock Exchange	TAI
Turkey	TR	Istanbul Stock Exchange	IST
United Kingdom	GB	London Stock Exchange	LON
United States	US	New York Stock Exchange; NASDAQ; NYSE Market	NYS, NAS, ASE

OA III: Construction of Annual Reports for non-US Global Firms

	Firm-year observations	# of unique firms
Firms' annual reports from LSEG Workspace between fiscal year 2008 and 2022	208,298	13,996
Sample after deleting the annual reports that cannot be parsed	205,299	13,913
Sample after deleting duplicated annual reports	199,125	13,913
Sample after keeping one annual report per firm per fiscal year		
deleting the "Prelim-FullYear" annual reports if the firm has 'FullYear" and "Prelim-FullYear" annual reports at the same fiscal ending date	163,920	13,913
keep the annual reports with the largest number of words per fiscal ending date	137,159	13,913
keep the annual reports with the most recent fiscal ending date per fiscal year	136,005	13,913

OA IV: Climate Change Disclosure Score Calculation

This part provides a 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. To create a global TCFD-aligned climate change vocabulary, we consider the ten largest TCFD supporters in each sector in each country[1] as a training sample that discloses climate change information aligned with the TCFD recommendations.

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 (e.g., Buehlmaier and Whited (2018), Engle et al. (2020)). We impose two search criteria for these company reports: (1) the most recent report over the sample period is selected for each TCFD supporting firm; 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 180 TCFD-aligned reports that contain textual TCFD-aligned climate change information. 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 as follows.

First, the extracted climate disclosure texts are structurally processed by removing punctuation and stop words, stripping white space, and stemming words (Gentzkow, Kelly and Taddy (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

[1] Not all sectors have at least ten TCFD supporters in each country.

climate disclosure in each company report has four subsections, namely, governance, strategy, risk management, and metrics and 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 to form a numerical vector. These words and their frequencies are defined as a category-specific climate change vocabulary. Finally, we aggregate the four category-level vocabularies to establish an overall climate change vocabulary.

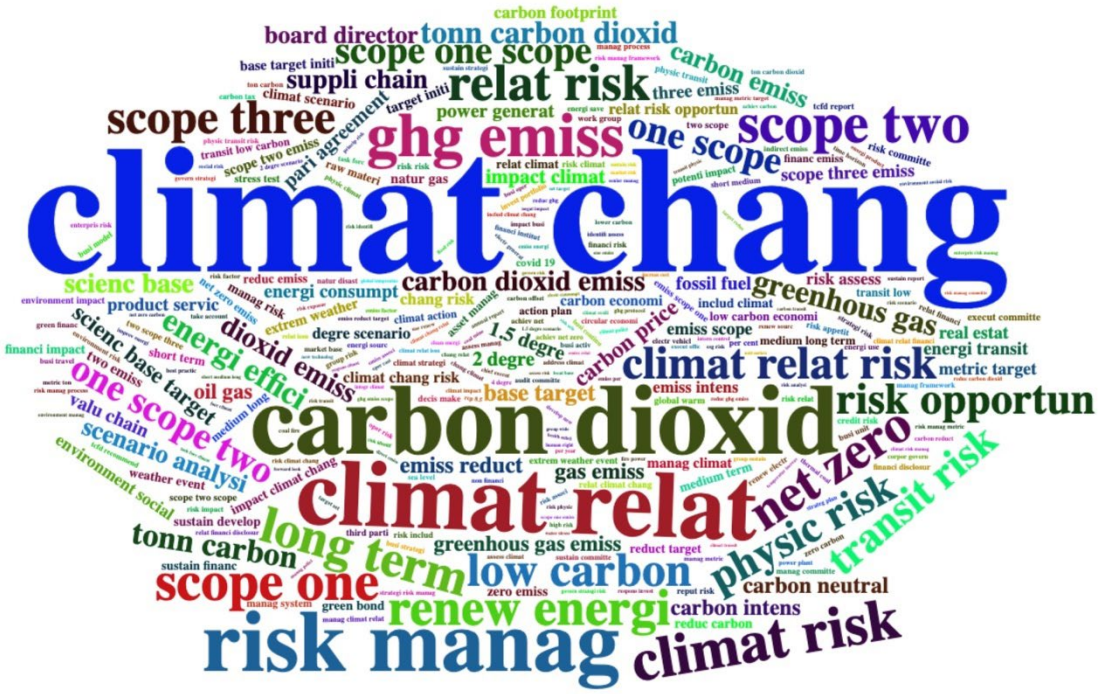


Figure OA1: Word Cloud of Climate Change Vocabulary

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 disclosure. 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 the firm's annual report

$$\begin{array}{cc} & \overbrace{\begin{matrix} \text{CCV's frequency} & & \text{Firm i's frequency} & & \end{matrix}}^{} \\ \begin{matrix} \text{N-dimensional} \\ \text{Vector} \end{matrix} & \begin{matrix} \text{Term}_1 \\ \text{Term}_2 \\ \text{Term}_3 \\ \vdots \\ \text{Term}_n \end{matrix} \begin{Bmatrix} f_{t_1,ccv} & f_{t_1,1,j} & f_{t_1,2,j} & \cdots & f_{t_1,i,j} \\ f_{t_2,ccv} & f_{t_2,1,j} & f_{t_2,2,j} & \cdots & f_{t_2,i,j} \\ f_{t_3,ccv} & f_{t_3,1,j} & f_{t_3,2,j} & \cdots & f_{t_3,i,j} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_{t_n,ccv} & f_{t_n,1,j} & f_{t_n,2,j} & \cdots & f_{t_n,i,j} \end{Bmatrix} \\ & \underbrace{\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad}_{D} \end{array}$$

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 (e.g., Te Liew, Adhitya and Srinivasan (2014), Hansen, McMahon and Prat (2017) and Gentzkow, Kelly and Taddy (2019)). 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:

$$\text{N-dimensional Vector} \quad \begin{matrix} \\ \text{Term}_1 \\ \text{Term}_2 \\ \text{Term}_3 \\ \vdots \\ \text{Term}_n \end{matrix} \quad \begin{matrix} \text{CCV's vector} \\ \\ \\ \\ \\ \end{matrix} \quad \begin{matrix} \\ \\ \\ \\ \\ \end{matrix} \quad \begin{matrix} \text{Firm i's vector} \\ \\ \\ \\ \\ \end{matrix} \quad \begin{matrix} \\ \\ \\ \\ \\ \end{matrix} \quad \begin{matrix} \\ \\ \\ \\ \\ \end{matrix} \quad \begin{Bmatrix} tf_idf_{t_1,CCV} & tf_idf_{t_1,1,j} & tf_idf_{t_1,2,j} & \cdots & tf_idf_{t_1,i,j} \\ tf_idf_{t_2,CCV} & tf_idf_{t_2,1,j} & tf_idf_{t_2,2,j} & \cdots & tf_idf_{t_2,i,j} \\ tf_idf_{t_3,CCV} & tf_idf_{t_3,1,j} & tf_idf_{t_3,2,j} & \cdots & tf_idf_{t_3,i,j} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ tf_idf_{t_n,CCV} & tf_idf_{t_n,1,j} & tf_idf_{t_n,2,j} & \cdots & tf_idf_{t_n,i,j} \end{Bmatrix}$$

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

$$CCSS_{i,j} = cosine\left(tf_idf_{t_n,i,j}, tf_idf_{t_n,ccv}\right) = \frac{tf_idf_{t_n,i,j} \cdot tf_idf_{t_n,ccv}}{|tf_idf_{t_n,i,j}|\,|tf_idf_{t_n,ccv}|}$$
$$= \frac{\sum_{n=i}^{N}(tf_{idf_{t_n,i,j}} * tf_idf_{t_n,ccv})}{\sqrt{(\sum_{n=1}^{N} tf_idf_{t_n,i,j})^2}\sqrt{(\sum_{n=1}^{N} tf_idf_{t_n,ccv})^2}}$$

We designate this climate change disclosure measure as the Climate Change Similarity Score (*CCDS*).

OA V: Validation Test of Climate Change Disclosure Measures

Table OA4: The Anatomy of Climate-related Financial Disclosure among 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, *CCDS* is the firm-level aggregated climate change disclosure variable. *Post* is a dummy variable, equal to one for firm-year observations after June 2017 and zero otherwise. The *t-statistics* in parentheses are adjusted by standard errors clustered at the country level. *, **, *** represent the 10%, 5% and 1% significance level, respectively.

Dependent Variable = CCDS			
TCFDSupporter*Post	1.246***	1.328***	0.933***
	(8.96)	(8.55)	(8.00)
LogAT	0.23	0.308	0.485
	(0.44)	(0.54)	(1.13)
LogBM	-0.009	-0.002	-0.018
	(-0.30)	(-0.08)	(-0.42)
ROA	-0.131**	-0.075	-0.059
	(-2.46)	(-1.12)	(-1.38)
Leverage	-0.422***	-0.350***	-0.181*
	(-4.14)	(-2.87)	(-1.77)
PPE	0.004	0.003	0.075
	(0.03)	(0.01)	(0.52)
Capx	-0.042	0.001	-0.004
	(-0.99)	(0.02)	(-0.08)
Dividend	-0.084	-0.171	0.053
	(-0.77)	(-1.15)	(0.96)
#Analysts	0.034	0.042	-0.032
	(0.27)	(0.21)	(-0.25)
Sample	Full Sample	CCDS>0	2015-2019
Adjusted R2	0.68	0.66	0.75
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	88,233	40,313	30,123

Table OA5: The Anatomy of Climate Risk's Effects on Climate-related Financial Disclosures

This table presents the regression results of climate change disclosure measure on firm-level carbon emissions. The dependent variable, *CCDS*, is the aggregate firm-level climate change disclosure variable. *LogEmission* is measured by the natural logarithm of total Scope 1, 2 and 3 emissions. *EmissionIntensity* is calculated as total Scope 1, 2 and 3 emissions scaled by firm's revenue in US dollars. *ESGScore* and *EnvironmentalScore* are the ESG and Environmental scores from the LSEG ESG database. CC^{risk} is climate change risk measure, calculated by the frequency of bigrams related to climate change together with the words "risk" or "uncertainty" in the earnings conference call. $CC^{exposure}$ is climate change exposure measure, calculated by the frequency of bigrams related to climate change in the earnings conference call. Controls are *LogAT, LogBM, ROA, Leverage, PPE, Capx, Dividend and #Analysts*. The *t-statistics* in parentheses are adjusted by standard errors clustered at the country level. *, **, *** represent the 10%, 5% and 1% significance level, respectively.

Dependent Variable = CCDS						
LogEmission	1.724***					
	(5.62)					
EmissionIntensity		0.343***				
		(4.00)				
ESGScore			0.599**			
			(2.48)			
EnvironmentalScore				0.411*		
				(1.83)		
CC^{risk}					0.237***	
					(3.76)	
$CC^{exposure}$						0.706***
						(4.72)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full Sample	Full Sample	Full Sample	Full Sample	Full Sample	Full Sample
Adjusted R2	0.70	0.70	0.70	0.70	0.73	0.73
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,416	44,416	43,278	43,278	40,855	40,855

Table OA6: The Anatomy of Article173's Effects on Climate-related Financial Disclosures

This table reports the results of the validation tests relating to climate change disclosures based on the changes in *CCDS* around the passage of Article 173 in France. In 2015, France passed *Article 173*, as a part of the *Energy Transition Act,* mandating climate change disclosure for institutional investors (*Article 173-IV*). The dependent variable is firm-level *CCDS. IOFrance* is the percentage of equity ownership held by French institutional investors in our sample and *Post* is a dummy variable, which is equal to one from 2015 onwards and zero otherwise. The *t-statistics* in parentheses are adjusted by standard errors clustered at the country level. *, **, *** represent the 10%, 5% and 1% significance levels, respectively.

Dependent Variable = CCDS				
IOFrance*Post$_{Article\ 173}$	0.863***	0.510***	0.907***	1.896***
	(4.64)	(2.71)	(4.04)	(2.75)
IOFrance	-0.703***	-0.383***	-0.783***	-0.774*
	(-4.77)	(-4.16)	(-2.87)	(-1.87)
LogAT	-0.051	-0.096	0.035	3.014***
	(-0.09)	(-0.17)	(0.05)	(3.46)
LogBM	0.008	0.002	0.144	0.592
	(0.06)	(0.01)	(0.70)	(1.52)
ROA	-0.144**	-0.144**	-0.079	0.009
	(-2.46)	(-2.39)	(-1.22)	(0.06)
Leverage	-0.451***	-0.428***	-0.339**	-0.452
	(-3.62)	(-3.52)	(-2.46)	(-1.32)
PPE	-0.126	-0.119	-0.187	-1.136***
	(-0.71)	(-0.67)	(-0.73)	(-3.40)
Capx	-0.039	-0.034	0.03	-0.115
	(-0.65)	(-0.53)	(0.51)	(-1.50)
Dividend	-0.069	-0.065	-0.126	0.024
	(-0.61)	(-0.56)	(-0.85)	(0.13)
#Analysts	0.089	0.11	0.134	-0.171
	(0.74)	(0.88)	(0.67)	(-0.77)
Sample	Full Sample	Non-French Sample	CCDS>0	IOFrance>=3%
Adjusted R2	0.67	0.66	0.66	0.74
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	83,151	80,511	38,859	3,459

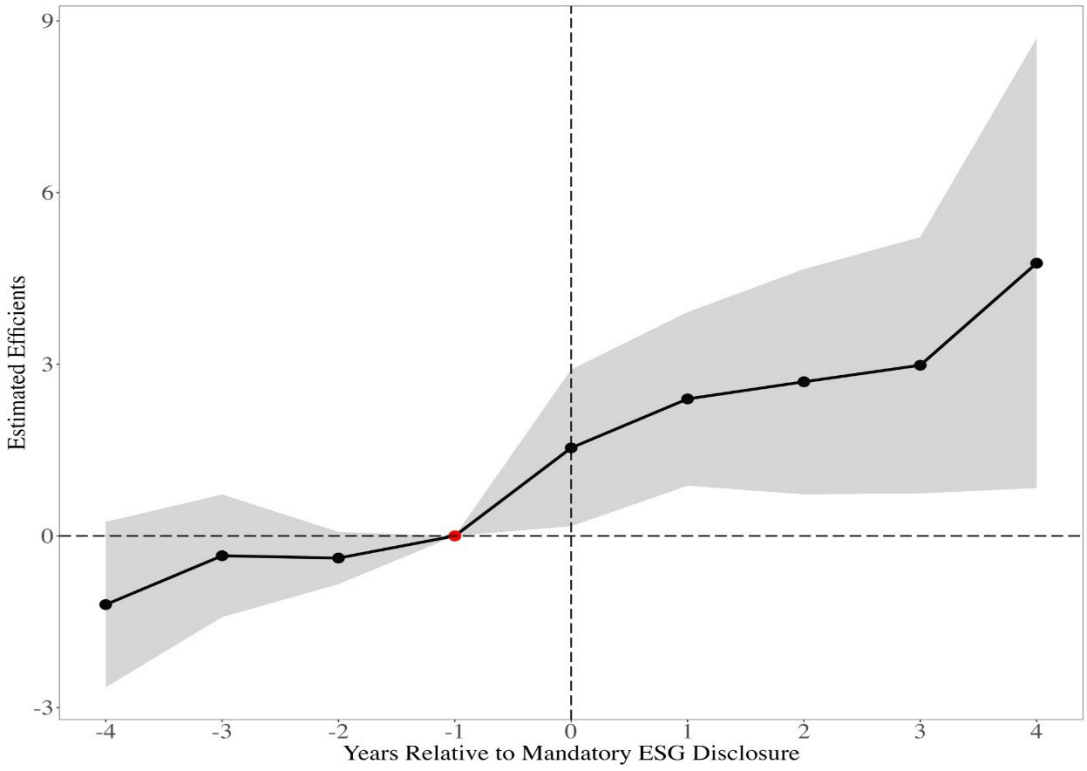
Table OA7: The Anatomy of Mandatory ESG Regulation' Effects on Climate-related Financial Disclosures

This table reports the regression results of the effects of mandatory ESG disclosure regulation on climate change disclosures using multiple DiD estimators. $Post_{Mandatory\ ESG}$ is a dummy variable equal to one for all years after a country adopts mandatory ESG disclosure regulation at year t. The mandatory ESG regulation data is from Krueger, Sautner, Tang and Zhong (2024). Controls are *LogAT, LogBM, ROA, Leverage, PPE, Capx, Dividend and #Analysts*. The *t-statistics* in parentheses are adjusted by standard errors clustered at the country level. *, **, *** represent the 10%, 5% and 1% significance level, respectively.

Dependent Variable = CCDS						
	TWFE	TWFE	Callaway & Sant'Anna (2021)	Callaway & Sant'Anna (2021)	Stacked DiD	Stacked DiD
	[1]	[2]	[3]	[4]	[5]	[6]
$Post_{Mandatory\ ESG}$	3.03***	3.192**	3.606***	2.599***	1.936***	2.055***
	(2.91)	(2.29)	(3.01)	(2.73)	(3.28)	(2.69)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full Sample	CCDS>0	Full Sample	CCDS>0	Full Sample	CCDS>0
Firm FE	Yes	Yes	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	No	No
Firm-Cohort FE	No	No	No	No	Yes	Yes
Year-Cohort FE	No	No	No	No	Yes	Yes

Figure OA2: Dynamic Effects of Staggered Mandatory ESG Regulation on Climate Change Disclosures

This figure shows the estimated dynamic effects of mandatory ESG disclosure regulation on climate change disclosures. We use a nine-year window (from four years before to four years after the policy shocks). The black dots represent point estimates of the effect in each year, while the gray shaded area denotes the 95% confidence intervals. The red dot indicates the reference period, the year prior to the mandatory ESG regulation, normalized to zero for interpretation.



OA VI: Factor Construction for non-US Global Sample

Motivated by Fama and French (2015) proposing a five-factor model that adds profitability and investment factors, I construct time-series mimicking factors including stock market, size, value, profitability and investment factors in non-US countries as the five-factor model has been shown to digest more stock return anomalies.

Following Fama and French (1993, 2015), book value is defined as common equity plus balance-sheet deferred tax and investment tax credit; profitability is revenue, minus cost of goods, minus selling, general and administration expenses and minus interest expenses, divided by book value of equity; and investment is the total asset growth rate for the previous fiscal year. In June of each year *t*, size is measured by stock price multiplied by outstanding shares; book to market ratio is measured by the ratio of book value in fiscal year *t-1* to market capitalisation at December of year *t-1*; and profitability and investment are measured with the corresponding accounting data in fiscal year *t-1*[2]. Following the Fama and French (2017) constructing five risk factors in an international setting, we adopt a one-size-fits-all method of using the top 90% of total market capitalisation in the global sample, which corresponds approximately to the median value of NYSE stocks. That is, the largest stocks representing 90% of total market cap are allocated into the big size group and others to the small size group.

Then, we utilise a two-way sorting method and obtain the 30% and 70% percentile of the BM ratios, profitability, and investment from big size stocks in the global sample.

Next, four mimicking factor portfolios, SMB, HML, RMW, and CMA, are created from these 18 portfolios. SMB is the average monthly return on the nine small portfolios minus the average monthly return on the nine big portfolios; and HML is the average monthly return on the two value portfolios minus the average monthly return on the two growth portfolios. Like

[2] We use the most recent accounting data before June in each year, for example, especially for the accounting data with the fiscal ending month of March or April, since most of them will be released after June in the year t.

the HML factor, we construct the RMW factor as the difference of average return between two robust profitability portfolios and two weak profitability portfolios, and CMA as the difference of average return between two conservative investment portfolios and two aggressive investment portfolios.

Table OA8: Time-series Factor Pricing Test in the US

This table shows the time-series regressions of monthly returns of CCDS-sorted portfolios on the Fama-French five factor factors plus momentum factor (Panel A) and the HXZ q-factors (Panel B) for the US sample. The HXZ q-factors include market (MKT), size (ME), investment (I/A), return on equity (ROE) and Expected Growth (EG) factors. Panel D shows the time-series regressions for portfolios double sorted on CCDS and size. The Low-High column represents the portfolios that take a long (short) position in the percentile of portfolios with lowest (highest) values. The Zero-High column represents the portfolios that take a long (short) position in the percentile of portfolios with zero (highest) CCDS values. The estimated factor loadings and risk-adjusted returns are reported in percentage. The t-statistics in parentheses are calculated based on the standard errors corrected by the Newey-West with 12 lags. The samples span over a period between July 2009 and December 2023. *, **, *** indicate the 10%, 5% and 1% significance level, respectively.

Panel A: FF5 +Momentum	Zero	Low	Median	High	Low-High	Zero-High
α	0.604[8.75]***	0.805[5.01]***	0.426[6.56]***	0.121[1.06]	0.684[3.95]***	0.483[3.39]***
MKT	0.998[46.64]***	1.042[35.07]***	0.973[40.72]***	0.876[32.88]***	0.166[4.27]***	0.122[3.09]***
SMB	0.074[1.98]**	0.034[0.57]	-0.101[-2.46]**	-0.065[-1.11]	0.099[1.42]	0.139[1.60]
HML	-0.240[-7.76]***	-0.322[-5.01]***	-0.110[-3.04]***	0.132[2.00]**	-0.454[-4.44]***	-0.373[-4.70]***
RMW	-0.076[-1.73]*	-0.005[-0.07]	0.149[2.51]**	0.167[3.03]***	-0.173[-1.52]	-0.244[-3.83]***
CMA	0.050[1.06]	0.217[1.30]	0.112[1.49]	0.191[2.05]**	0.026[0.11]	-0.141[-1.33]
MOM	0.008[0.36]	-0.146[-3.38]***	-0.002[-0.06]	-0.010[-0.28]	-0.137[-2.51]**	0.017[0.36]
Observations	174	174	174	174	174	174
Adj-R2	0.96	0.88	0.93	0.88	0.37	0.42
Panel B: HXZ q-factor	Zero	Low	Median	High	Low-High	Zero-High
α	0.613[8.14]***	0.820[5.31]***	0.416[4.97]***	0.160[1.21]	0.661[3.52]***	0.454[2.64]***
MKT	0.981[51.45]***	1.061[31.30]***	0.997[41.98]***	0.899[28.51]***	0.161[4.11]***	0.082[1.84]*
ME	0.053[1.42]	-0.053[-0.86]	-0.138[-3.08]***	-0.152[-2.63]***	0.098[1.00]	0.205[2.72]***
I/A	-0.125[-2.82]***	-0.084[-0.54]	0.041[0.98]	0.294[4.44]***	-0.378[-1.97]*	-0.419[-4.66]***
ROE	-0.149[-3.28]***	-0.045[-0.40]	0.032[0.49]	0.095[1.67]*	-0.141[-1.12]	-0.245[-2.78]***
EG	0.184[2.28]**	0.033[0.23]	0.115[1.75]*	-0.169[-1.97]**	0.202[1.06]	0.354[2.32]**
Observations	174	174	174	174	174	174
Adj-R2	0.95	0.86	0.93	0.88	0.24	0.34

Table OA9: Double Sorting on Size and CCDS

This table shows the time-series regressions of monthly returns of portfolios double sorted on size and CCDS for the Global sample (Panel A), the USA sample (Panel B) and the Global ex USA sample (Panel C). The Low-High column represents the portfolios that take a long (short) position in the percentile of portfolios with lowest (highest) values. The estimated risk-adjusted returns are reported in percentage. The t-statistics in parentheses are calculated based on the standard errors corrected by the Newey-West with 12 lags. The samples span over a period between July 2009 and December 2023. *, **, *** indicate the 10%, 5% and 1% significance level, respectively.

	Small Size			**Big Size**		
	Low	High	Low-High	Low	High	Low-High
Observations	174	174	174	174	174	174
Panel A: Global Sample						
α	1.777***	1.375***	0.403**	0.896***	0.494***	0.402***
	(9.33)	(8.14)	(2.25)	(7.43)	(5.61)	(3.54)
Adj-R2	0.79	0.78	0.03	0.87	0.83	0.29
Panel B: US Sample						
α	1.294***	1.253***	0.041	0.729***	0.099	0.630***
	(7.26)	(4.96)	(0.23)	(4.50)	(0.86)	(3.54)
Adj-R2	0.93	0.79	0.08	0.86	0.88	0.34
Panel C: Global ex US Sample						
α	0.910***	0.470**	0.441***	0.334*	0.091	0.243**
	(3.16)	(2.31)	(2.63)	(1.87)	(0.77)	(2.33)
Adj-R2	0.55	0.62	0.06	0.57	0.65	0.10

Table OA10: Subsample Analysis

This table presents empirical regression results examining the relationship between climate change disclosure score and stock return. Panel A reports the time-series regressions of portfolios sorted on CCDS for the global sample before and after June 2017. Panel B reports FM cross-sectional regression estimates using the following one-, three-, and six- returns, denoted by RET_1M, RET_3M, RET_6M as dependent variables, respectively. *t-statistics* are reported in parentheses. *, **, *** indicate the 10%, 5% and 1% significance level, respectively.

Panel A: Factor Pricing Model						
	Low	High	Low-High	Low	High	Low-High
α	0.903***	0.501***	0.402***	1.057***	0.651***	0.406*
	(7.58)	(4.31)	(4.49)	(4.89)	(6.84)	(1.72)
Sample	Global sample before June 2017			Global sample after June 2017		
Observations	96	96	96	78	78	78
Adj-R2	0.88	0.81	0.13	0.90	0.87	0.47
Panel B: FM Test						
	RET_1M	RET_3M	RET_6M	RET_1M	RET_3M	RET_6M
CCSS	-0.074***	-0.073***	-0.078***	-0.148**	-0.150***	-0.153***
	(-2.97)	(-3.27)	(-3.83)	(-2.52)	(-2.78)	(-2.70)
LogME	-0.376***	-0.360***	-0.357***	-0.016	-0.052	-0.034
	(-3.29)	(-2.96)	(-2.88)	(-0.07)	(-0.23)	(-0.16)
LogBM	0.026	0.037	0.028	-0.046	-0.057	-0.032
	(0.42)	(0.62)	(0.50)	(-0.74)	(-0.99)	(-0.61)
ROE	0.181***	0.175***	0.179***	0.184**	0.177**	0.184***
	(3.76)	(3.94)	(4.53)	(2.46)	(2.53)	(2.89)
Investment	-0.230***	-0.227***	-0.227***	-0.164***	-0.173***	-0.170***
	(-5.97)	(-5.49)	(-5.45)	(-3.78)	(-3.64)	(-3.25)
RetPrior12M	0.321***	0.364***	0.333***	0.299***	0.423***	0.412***
	(2.66)	(3.40)	(3.57)	(3.45)	(4.73)	(4.58)
RetVolPrior12M	-0.161	-0.205**	-0.215**	-0.041	-0.05	-0.038
	(-1.52)	(-2.24)	(-2.57)	(-0.24)	(-0.29)	(-0.23)
PPE	-0.128	-0.117	-0.113	0.178**	0.164*	0.165**
	(-1.44)	(-1.35)	(-1.35)	(2.06)	(1.93)	(2.00)
Leverage	0.101*	0.106**	0.111**	-0.05	-0.038	-0.046
	(1.71)	(2.11)	(2.38)	(-0.91)	(-0.69)	(-0.91)
WWIndex	-0.336***	-0.297***	-0.297***	-0.217	-0.236	-0.253
	(-3.40)	(-3.08)	(-2.87)	(-1.08)	(-1.26)	(-1.46)
Sample	Global sample before June 2017			Global sample after June 2017		
Observations	2043	2043	2043	4150	4150	4150

OA VII: Factor Loading Estimates

In each month t, we define N as the number of stocks represented by i ; l as N x 1 matrix of 1's; β as the N x J matrix of betas; Z as the N x K matrix of firm characteristics; and R^e as stock return in excess of the risk-free rate. We estimate FM cross-sectional regressions in each month t by:

$$R_{i,t}^e = \alpha_t + \sum_{j=1}^{J} \lambda 1_t \beta_{i,j,t} + \sum_{k=1}^{K} \lambda 2_t Z_{i,j,t} + \varepsilon_{i,t}$$

Let

$$X_t = (l_t : \widehat{\beta_t} : Z_t)$$

The basic OLS regression produces cross-sectional coefficients: $\phi^{OLS} = (\hat{\alpha} : \widehat{\lambda 1_t} : \widehat{\lambda 2_t})$ estimated by

$$\phi_t^{OLS} = ({X_t}' X_t)^{-1} {X_t}' R_t^e$$

However, one of the OLS regression assumptions for unbiased coefficients does not always hold, which relates to homoscedasticity (i.e., $var(\varepsilon_i|X) = \sigma^2$) for each stock. This implies biased coefficient estimates. Hence, Chordia, Goyal and Shanken (2017) provide the EIV-corrected measure of beta estimates by:

$$\phi_t^{EIV} = ({X_t}' X_t - \sum_{i=1}^{N} M' \Sigma_{\widehat{\beta}_{i,t}} M)^{-1} {X_t}' R_t^e$$

M is a matrix defined as

$$\mathrm{M} = \left(0_{J*1} : I_{J*J} : 0_{J*K}\right)$$

The I is an identity matrix and $\Sigma_{\widehat{\beta}_{i,t}}$ represents the heteroscedasticity consistent variance-covariance matrix of beta estimate for each stock.

Table OA11: FM Test with Factor Loading

This table presents the results of monthly FM regressions of individual stock monthly excess returns on factor betas and additional firm characteristics. Betas are estimated based on Fama-French five factor pricing model from a time-series rolling window over past two years with at least 300 daily returns in each month. The estimated betas are corrected for the error-in variable bias. At each firm-month level, the dependent variable is the average monthly return over the subsequent one and twelve months, respectively. All independent variables are winsorised at 1% and 99% level and standardized with zero mean and one-unit standard deviation. In each month, we conduct the cross-sectional regression of monthly return on estimated betas and additional firm characteristics. The average time-series coefficients from monthly regressions are reported and the *t-statistics* in parenthesis are calculated as average coefficients divided by the Newey-West standard errors with 12 lags. The observations are the average number of individual stocks in monthly cross-sectional regressions. The sample period is between July 2009 and December 2023.

	Global Sample		US Sample		Global ex US Sample	
	RET_1M	RET_12M	RET_1M	RET_12M	RET_1M	RET_12M
CCDS	-0.089***	-0.094***	-0.165***	-0.174***	-0.068*	-0.066*
	(-2.73)	(-2.79)	(-4.73)	(-5.48)	(-1.81)	(-1.82)
β^{Mkt}	0.022	0.043	0.142	0.144	0.005	0.025
	(0.26)	(0.65)	(0.85)	(1.21)	(0.06)	(0.36)
β^{SMB}	0.072	0.035	-0.016	-0.005	0.083	0.041
	(0.99)	(0.71)	(-0.08)	(-0.05)	(1.10)	(0.76)
β^{HML}	0.123	0.08	0.318	0.198	0.143*	0.091
	(1.34)	(1.17)	(1.18)	(1.06)	(1.75)	(1.46)
β^{CMA}	0.112	0.066	0.635**	0.396*	0.098	0.062
	(1.50)	(1.14)	(2.11)	(1.96)	(1.62)	(1.38)
β^{RMW}	0.098**	0.117***	0.051	0.145	0.090*	0.107***
	(2.04)	(3.20)	(0.44)	(1.19)	(1.83)	(2.76)
LogME	0.009	0.012	0.042	0.05	-0.023	-0.013
	(0.13)	(0.21)	(0.35)	(0.52)	(-0.31)	(-0.21)
LogBM	0.043	0.072*	0.1	0.133**	0.015	0.052
	(1.02)	(1.87)	(1.64)	(2.21)	(0.28)	(1.09)
RetPrior12M	0.343***	0.395***	0.104	0.161**	0.412***	0.465***
	(4.80)	(6.52)	(1.43)	(2.44)	(5.71)	(7.63)
RetVolPrior12M	-0.215***	-0.228***	0.139	0.008	-0.292***	-0.294***
	(-4.15)	(-4.06)	(1.31)	(0.09)	(-5.27)	(-4.89)
Investment	-0.156***	-0.167***	-0.009	-0.033	-0.183***	-0.193***
	(-5.80)	(-5.88)	(-0.18)	(-0.78)	(-5.51)	(-6.01)
ROE	0.182***	0.179***	0.132**	0.122**	0.197***	0.193***
	(5.11)	(5.98)	(2.25)	(1.99)	(4.52)	(5.71)
Observations	3063	3063	750	750	2312	2312

Table OA12: FM Test with Short-term Return

This table presents the results of monthly FM regressions of individual stock monthly excess returns on climate change disclosure (CCDS) and firm characteristics. The firm characteristics are market capitalization and book-to-market ratio, past twelve-month return, return volatility, investment, profitability, leverage ratio, property plant and equipment, and financial constraints. At each firm-month level, the dependent variable is the average monthly return over the three and six months, respectively. All independent variables are winsorised at 1% and 99% level and standardized with zero mean and one-unit standard deviation. In each month, we conduct the cross-sectional regressions of monthly returns on CCDS and firm characteristics. The average coefficients from monthly regressions are reported and the t-statistics in parenthesis are calculated as average coefficients divided by the Newey-West standard errors with 12 lags. The observations are the average number of individual stocks in monthly cross-sectional regressions. The sample period is between July 2009 and December 2023.

	Global Sample		US Sample		Global ex US Sample	
	RET_3M	RET_6M	RET_3M	RET_6M	RET_3M	RET_6M
CCDS	-0.108***	-0.113***	-0.143***	-0.153***	-0.069**	-0.071**
	(-3.89)	(-3.85)	(-2.70)	(-2.88)	(-2.10)	(-2.11)
LogME	-0.219*	-0.209*	-0.066	-0.084	-0.346***	-0.331***
	(-1.78)	(-1.72)	(-0.66)	(-0.88)	(-2.74)	(-2.68)
LogBM	-0.005	0.002	0.141*	0.152*	-0.041	-0.038
	(-0.11)	(0.04)	(1.75)	(1.91)	(-0.86)	(-0.85)
ROE	0.173***	0.179***	0.180**	0.164**	0.161***	0.175***
	(4.48)	(5.12)	(2.41)	(2.39)	(4.03)	(4.74)
Investment	-0.202***	-0.201***	-0.105**	-0.100**	-0.212***	-0.214***
	(-6.11)	(-5.75)	(-2.13)	(-2.09)	(-6.09)	(-6.25)
RetPrior12M	0.390***	0.369***	0.101	0.116	0.468***	0.431***
	(5.48)	(5.61)	(1.22)	(1.43)	(6.89)	(6.86)
RetVolPrior12M	-0.136	-0.137	0.027	0.011	-0.224**	-0.223**
	(-1.44)	(-1.49)	(0.20)	(0.09)	(-2.42)	(-2.44)
PPE	0.01	0.012	-0.094	-0.08	0.036	0.033
	(0.13)	(0.17)	(-1.08)	(-0.98)	(0.52)	(0.47)
Leverage	0.041	0.04	0.175***	0.170***	-0.017	-0.013
	(0.97)	(1.00)	(3.03)	(2.89)	(-0.38)	(-0.31)
WWIndex	-0.268***	-0.275***	-0.164	-0.190*	-0.341***	-0.344***
	(-2.71)	(-2.83)	(-1.53)	(-1.91)	(-3.06)	(-3.27)
Observations	2987	2987	740	740	2248	2248

OA VIII: The Channel of Cost of Equity

Table OA13: The Channel of Cost of Equity

This table shows the regression results of the effects of firm-level climate change disclosure on the information environment for the subsample with CCDS greater than zero. *Bid-Ask Spread*, *Amihud's Illiquidity (AIM)* and *the number of zero return (ZeroRet)*. *Bid-Ask Spread* is the natural logarithm of the median value of the difference between daily closing bid and ask prices divided by the midpoint in a year. *Amihud's Illiquidity* is calculated as the natural logarithm of the median value of the daily absolute stock returns divided by daily dollar trading volumes in US millions over a year. *ZeroRet* is the number of trading days with zero returns scaled by the potential trading days over a year. *ImpliedCOE* is calculated as the average value of four measures: Easton's PEG model (2004), Gebhardt et al. (2001), Claus and Thomas (2001) and Ohlson and Juettner-Nauroth (2005)'s model. *RetVol* as the standard deviation of daily stock return over a one-year window. *FError* is measured as the average value of the absolute difference between analyst mean estimates and actual earnings, then scaled by stock price at the beginning of the year. The *t-statistics* in parentheses are adjusted by the clustered standard error at the firm level. *, **, *** represent the 10%, 5% and 1% significance level, respectively

	Liquidity			Uncertainty			COE
	Bid-ask Spread	AIM	ZeroRet	RetVol	FError(0)	FError(1)	ImpliedCOE
CCSS	-0.023***	-0.008***	-0.011**	-0.030***	-0.049**	-0.054**	-3.099***
	(-4.95)	(-2.68)	(-2.10)	(-5.34)	(-2.30)	(-2.41)	(-3.80)
LogAT	-0.364***	-0.490***	-0.303***	-0.084**	-1.115***	-1.345***	-22.850***
	(-14.63)	(-27.43)	(-9.62)	(-2.53)	(-9.77)	(-10.45)	(-4.66)
LogBM	0.168***	0.189***	0.137***	0.169***	1.171***	1.055***	21.123***
	(26.84)	(37.92)	(13.34)	(16.42)	(32.16)	(28.97)	(13.38)
ROA	-0.051***	-0.037***	-0.052***	-0.076***	-0.179***	-0.149***	-6.494***
	(-10.88)	(-10.78)	(-6.12)	(-9.69)	(-6.60)	(-5.56)	(-4.69)
Capx	-0.008*	0.004	-0.021***	0.006	-0.012	-0.012	0.093
	(-1.66)	(1.12)	(-3.16)	(0.89)	(-0.45)	(-0.44)	(0.08)
PPE	0.026**	0.018**	-0.002	0.014	0.08	0.145**	1.842
	(2.25)	(1.98)	(-0.11)	(0.81)	(1.26)	(2.15)	(0.70)
Leverage	0.070***	0.096***	0.047***	0.143***	0.512***	0.370***	13.096***
	(9.70)	(17.54)	(4.72)	(13.62)	(14.36)	(9.68)	(7.37)
WWIndex	0.012**	0.011**	0.014	-0.002	-0.029	0.0002	5.479**
	(2.08)	(2.22)	(1.21)	(-0.35)	(-0.63)	(0.00)	(2.28)
#Analyst	-0.051***	-0.050***	-0.045***	0.002	-0.113***	-0.112**	-2.012
	(-6.66)	(-8.04)	(-4.26)	(0.15)	(-2.79)	(-2.51)	(-1.25)
RetVolPrior12M	-0.011***	-0.012***	-0.023***	0.064***	0.094***	-0.025	9.712***
	(-3.17)	(-4.69)	(-4.43)	(11.35)	(4.15)	(-1.08)	(9.94)
Sample	CCSS>0	CCSS>0	CCSS>0	CCSS>0	CCSS>0	CCSS>0	CCSS>0
Adjusted R2	0.91	0.95	0.83	0.74	0.56	0.53	0.58
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,017	36,017	36,017	36,844	33,056	27,733	29,605

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