Climate Change Disclosure and Capital Market Dynamics: Evidence from the UK Equity Market

Thesis submitted in partial fulfilment of the requirements for the degree

Doctor of Philosophy

ICMA Centre

Henley Business School

University of Reading

Alessio Venturini

August 2025

Declaration

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

Alessio Venturini

August 20, 2025

Acknowledgements

I would like to express my deepest gratitude to my supervisors, Professor Simone Varotto and Dr. Alfonso Dufour, for their invaluable guidance throughout my PhD journey. Their combined expertise, encouragement, and continuous feedback have been instrumental in shaping my research and academic development. Professor Varotto's supportive demeanour, patient guidance, and profound knowledge have greatly contributed to all aspects of my research. His willingness to support a one-year extension of my PhD to allow me to work at the Bank of England during my studies was deeply appreciated. Similarly, Dr. Dufour's insightful support, meticulous attention to details, and thoughtful advice consistently pushed me to improve and innovate in my research.

I am also immensely grateful to the ICMA Centre for providing financial support and resources, as well as to its staff for their assistance and encouragement throughout my PhD. Their support created an environment in which I could thrive both academically and personally.

I owe a profound debt of gratitude to my family, especially my father, mother, and younger sister. Being the first in my family to pursue a PhD is a milestone I am proud to share with them. Their belief in my abilities and their constant support have been the foundation of this achievement, and I am deeply thankful for everything they have given me. I am particularly indebted to my partner, Aybüke Naz, for her companionship and emotional support during this significant phase of my life. Without her, I may never have chosen an academic path, and I look forward to sharing our future life together.

Finally, to my friends, especially Amir, Eike, Emanuele, Evripidis, Gianluca, Lambis, Massimo, Meysam, Samuele, Zeynep, Zhenghong, and all others, thank you for your unwavering support, friendship, and understanding throughout this journey. Your encouragement has been a constant source of strength and motivation.

Abstract

This thesis examines how investors price firm-level climate change disclosures and the role of investor preferences for such disclosures within the UK equity market. The first and second empirical chapters investigates the effect of physical climate risk disclosure and climate adaptation disclosures on firm value around natural disaster events. Using textual analysis of annual reports issued between 1996 and 2018 by UK listed firms, I demonstrate that the disclosure of material exposure to physical climate risks mitigates the negative effects of natural disasters on firm value. However, I observe that disclosing climate adaptation measures does not have any mitigating effect on firm value. Further tests show that this heterogeneous response to climate-related disclosures arises from their asymmetric effects on investor uncertainty.

The third empirical chapter analyses the preferences of institutional investors who are signatories to the United Nations Principles for Responsible Investment (UN PRI) for climate disclosures that are finan-

cially material. Leveraging the ClimateBERT large language model to classify material climate commitments in UK firms' annual reports, I find that UN PRI investors induce investee firms to disclose such information, particularly commitments related to climate transition risks rather than physical climate risks. Moreover, I show that disclosures induced by UN PRI investor engagement are relevant for capital markets, as they enhance the informational content of annual reports and are associated with higher analyst forecast accuracy.

This thesis contributes to the field of climate finance by providing novel evidence from the UK equity market. Specifically, it highlights the firm-level valuation benefits of transparency regarding physical climate risks, the limitations associated with climate adaptation disclosures, and the critical role of responsible investors in promoting the disclosure of material climate commitments. The findings have significant implications for corporate disclosure practices, investor stewardship, and regulatory initiatives aimed at fostering climate-resilient financial markets.

Keywords: Climate Change Risks, Climate Risk Disclosure, Climate Adaptation Disclosure, Responsible Investment, Asset Pricing.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Over recent decades, climate change has emerged as a defining challenge for financial markets, presenting risks and opportunities that impact firm-level operations and valuations. Amid escalating climate risks, from extreme weather events to intensifying regulatory pressure for a transition to a low-carbon economy, investors are increasingly demanding granular information on how firms are exposed to, and prepared for, the current and future impacts of climate change risks. Such information is particularly relevant for equity market efficiency, as it enables investors to allocate capital optimally and to price climate-related risks and opportunities accurately (Ilhan et al., 2023a). In response to these investor demands, regulatory bodies and initiatives such as the Task Force on Climate-related Financial Disclosures have urged firms to enhance the transparency of their climate change reporting. Yet crucial questions remain unresolved: Do financial markets price firm-level climate risk disclosures, and if so, how? Do investors price disclosures of climate risk exposures differently from information on corporate responses to these risks? Do investors actively demand climate-related disclosures from their investee firms, and which types of information are they most interested in?

This thesis seeks to address these questions by focusing on firms publicly listed in the UK equity market. This market provides an unique context to empirically investigate how investors incorporate climate-related disclosures into their investment process for several reasons. First, regulatory policy in the UK frames climate disclosure at the firm level as a central tool for aligning corporate behaviour with the country's climate change commitments (Lorenzoni et al., 2007). Consequently, investors have shown increasing interest in climate-related information disclosed within corporate annual reports (Jouvenot and Krueger, 2022). Second, UK firms have historically been granted with considerable discretion in both the content and extent of their climate change related disclosures in their annual reports. This creates naturally a rich empirical setting to examine how investors price firm-level disclosures, given substantial variation in reporting practices across firms and sectors. Third, the UK's 2013–2014 clarification of fiduciary duties formally recognised that environmental, social, and governance (ESG) factors, including climate-related risks, should be integrated into the investment processes of institutional investors where financially material (Gibson Brandon et al., 2022). Taken together, these characteristics make the UK equity market an ideal setting in which to investigate how financial markets price various types of climate-related disclosures, and how investors' demand for such information influences corporate reporting behaviour and market outcomes.

To support the empirical analysis that follows, the thesis begins with a review about the emerging literature on climate finance. Building on the work of Venturini (2022), the review sets out the main theoretical frameworks to study how financial markets price climate-related risks. It also discusses the use of both top-down and bottom-up approaches to analyse dynamics connected to both asset pricing and corporate finance domains, and highlights the main empirical results that define the current state of research. In doing so, the literature review provides a theoretical and empirical foundation for studying the role of climate change disclosure in capital markets.

The first empirical chapter investigates how investors price firm-level disclosures of physical climate risk in the context of sudden climate-related shocks. I begin by constructing a textual measure of physical climate risk using a dictionary of terms associated with physical climate hazards (e.g., floods, storms) and by assessing the frequency of these terms in UK firms' annual reports. I validate this measure by showing that it correlates positively with the impact of natural disasters at the firm headquarters level, thus confirming that it can proxy for a firm's exposure to extreme weather events, a key determinant of physical climate risk. I then exploit natural disasters as exogenous shocks to information uncertainty (i.e., events that limit investors' ability to estimate firm value) to examine whether physical climate risk disclosure influences how investors price firms during such shocks. I find that firms disclosing information about their physical climate risks experience significantly smaller share price declines around natural disasters compared to affected firms that do not disclose such information. One potential explanation for this result is that investors reward firms for disclosing physical climate risk because such information mitigates investors' ambiguity during climate-related shocks. I validate this interpretation by examining stock liquidity around natural disaster events as a proxy for information uncertainty, finding that liquidity is indeed higher for impacted firms that are transparent about their physical climate risk exposures. Further analyses confirm the reduction in investors' ambiguity channel, as I do not find changes in the expected and realised cash flows or stock volatility. Overall, these results align with the predictions of Guay and Verrecchia (2018), whose theoretical framework suggests that disclosure of adverse information, such as exposure to physical climate risks, reduces investor uncertainty and stabilises firm valuations during periods of heightened information asymmetry.

An open question arising from the first empirical chapter is whether the observed benefits of physical climate risk disclosure stem from firms that also disclose their climate adaptation strategies, rather than merely acknowledging their risk exposures to investors. This question motivates the second empirical chapter, in which I construct a novel dictionary of climate adaptation verbs to distinguish between firms that disclose adaptation strategies (i.e., those that use such verbs in the textual proximity to physical climate risk terms) and those that only report on physical risk exposure without discussing adaptation actions. I validate these measures by demonstrating that, unlike the physical climate risk measure, the climate adaptation measure captures variation in future investment and sustainability outcomes, supporting the notion that the adaptation dictionary can proxy for climate adaptation efforts at the firm level. I then examine how investors price these types of disclosures strategies, applying a framework similar to that used in the first empirical chapter. Interestingly, I find that the valuation benefits of disclosure during natural disaster events are driven by firms that disclose only their exposure to physical climate risks. In contrast, affected firms that also report adaptation strategies do not reap the same benefits of disclosure. To explore the mechanisms underlying these findings, I again employ an asset pricing framework akin to that of the first empirical chapter. Consistent with the notion that only transparency regarding physical climate risk exposure reduces investor uncertainty, I find that stock liquidity following natural disasters decreases less only for firms that do not disclose adaptation strategies. Although initially counterintuitive, these results align with the notion that UK firms may historically have refrained from detailed adaptation disclosures to avoid potential costs arising from investor misinterpretation of such information. Evidence from interviews with managers of FTSE 100 and FTSE All-Share companies (firms included in my sample) supports this interpretation (Tang, 2022). Specifically, a key point from the Tang (2022) interviews is that *"communicating this information clearly and in positive terms can be difficult, and the potential for stakeholders to misinterpret information about climate risks and responses to them is considerable."*

The third empirical chapter explores how investors engage with climate change disclosures, focusing on the preferences of responsible versus traditional institutional investors. Specifically, I examine whether responsible investors, particularly those committed to the United Nations Principles for Responsible Investment (UN PRI), actively engage with their portfolio firms to demand climate disclosures that are financially material. For this analysis, I leverage the state-of-the-art capabilities of the domain-specific large language model introduced in Bingler et al. (2024), ClimateBERT, to classify statements regarding material climate-related commitments in UK annual reports. I additionaly refine ClimateBERT's classifications to distinguish between material commitments relating to transition risks and those addressing physical climate risks (Wagner et al., 2023). This enables me to differentiate, for example, between mitigation commitments aimed at reducing carbon emissions (transition risks commitments) and detailed adaptation commitments targeting flood risk (physical risks commitments). I find that UN PRI signatories exert significant influence over firms' decisions to disclose material commitments to managing climate risks. Notably, this influence is driven predominantly by disclosures concerning climate transition risks rather than physical risks. I establish the causal nature of this relationship using two identification strategies: an instrumental variables approach exploiting mechanical inclusion in the FTSE 350 index, and a difference-in-differences design leveraging the UK's 2013–2014 fiduciary duty clarification as a quasi-natural experiment. Both strategies confirm the baseline finding that responsible investors demand material commitments to manage climate (and in particular transition-related) risks, mitigating potential endogeneity concerns such as reverse causality and selection bias. Finally, I demonstrate that disclosures demanded by UN PRI investors convey value-relevant information to capital markets. To examine this, I exploit variation in disclosure induced by the interaction between UN PRI ownership and FTSE 350 index membership, a source of investor pressure exogenous to equity market outcomes. Using this instrumented variation, I show that disclosures of material climate commitments are associated with positive abnormal stock returns around annual report releases. Moreover, I find that such disclosures lead to lower analyst forecast errors, particularly over longer horizons. Importantly, in both analyses, the effects are driven by disclosures concerning material commitments to climate transition risks, consistent with the notion that both shareholders and analysts pay attention to disclosures emerging from UN PRI investor engagements. Overall, these findings are consistent with the literature documenting the informational value of voluntary sustainability disclosures (e.g., Ben-Amar et al. (2024)) and further refine our understanding by identifying investor-driven materiality as a key mechanism through which these benefits arise.

This thesis contributes to the field of climate finance and corporate disclosure by providing several important contributions. First, this thesis provides new empirical evidence from the UK equity market, a setting that has been comparatively underexplored in the climate finance literature, thus expanding our understanding beyond the predominantly US-focused studies (e.g., Berkman et al. (2024); Flammer et al. (2021); Nagar and Schoenfeld (2022), among others). Second, this thesis shows the tangible benefits of physical climate risk transparency, showing that disclosure of such risks can mitigate the adverse valuation effects of climate-related shocks by reducing investor uncertainty and enhancing market liquidity. Third, the thesis highlights critical limits to the effectiveness of corporate disclosure, revealing that while transparency regarding risk exposure is valued positively by investors, disclosures concerning climate adaptation strategies may be met with scepticism and do not necessarily translate into valuation benefits. Finally, the research shows the role of responsible institutional investors in actively shaping corporate climate disclosure practices. It shows that such investors can serve as active stewards, exerting meaningful influence to elicit material and financially relevant climate-related commitments from their investee firms (particularly in relation to climate transition risks). Collectively, these contributions improve our understanding of how financial markets process climate-related information and the ways in which disclosure, investor engagement, and market dynamics interact in the era of climate change risks.

Chapter 2

Literature Review about Climate Finance

2.1 Introduction

Climate change is shaping the sociological, geopolitical and financial dynamics of our time. The stark impact of sociological issues may be affected by changes in long-term climate variable patterns, with possible effects on food shortage and migration, particularly in developing countries (Dell et al., 2012). Geopolitical bargaining marking the path to a new green economy will result from a mixture of diplomatic scenarios that might dictate radical changes in our societies. Financial markets will also play a crucial role, as the shift to a green economy will also depend on monetary flows provided by governments and investors for such a metamorphosis (NGFS, 2020).

Although the scientific community has found that most of the climate change and related effects will be more evident in the future, some environmental and policy implications can already be seen today. For instance, in 2018, the first bankruptcy 'because of climate change' occurred in the US.[1] Moreover, McGlade and Ekins (2015) have argued that one-third of oil reserves, one half of gas reserves and 80% of coal reserves must remain unburned from 2010 to 2050 to meet the target of 2° warming set by the Paris Agreement. Similar results have been found in other studies, raising concerns about the serious threat of certain assets becoming 'stranded' (Semieniuk et al., 2021).[2]

These data are of interest for governments, which could be responsible for the coverage of public costs because of physical and transitional damages (Lamperti et al., 2019), and for financial actors as well. According to the Centre for the Study of Financial Innovation survey, climate change was ranked in 2019 as the second-highest risk factor for reinsurance companies and the third for non-life insurance firms.[3] Moreover, recent surveys have argued that these concerns also apply to banks and institutional investors (Amel-Zadeh, 2021; CFA, 2020; Krueger et al., 2020). Thus, if the world will not prepare itself to face (or at least *mitigate*) one of the most important challenges of this century, economic damages and social concerns will inevitably increase in the coming years.

These empirical facts can explain the 'momentum' climate change has recently gained in scientific debates and the consequent political efforts to concentrate the world's attention on this global issue. One of the most important events in this direction was the Conference of the Parties 21 (or Paris Agreement). Beyond the strict targets set for each country at an international level, finance played an important role in the agreement. In particular, the second article of the Paris Agreement expresses its goal of '*making finance flows consistent with a pathway towards low greenhouse gas emissions and climate-resilient development*'.[4]

[1] `https://www.wsj.com/articles/pg-e-wildfires-and-the-first-climate-change-\bankruptcy-11547820006`

[2] For a full review on this point, the reader is referred to Curtin et al. (2019).

[3] `https://www.csfi.org/insurance-banana-skins`

[4] UNFCCC Paris Agreement (2015)

The financial world seems to have accepted this challenge with efforts from policymakers[5], practitioners and academics, although the latter has been considered '*late to the game*' in recent years (Diaz-Rainey et al., 2017; Hong et al., 2020). Engagement with the financial industry, combined with the award of 2018's Nobel Prize in Economics to William Nordhaus (for his contributions on integrated assessment models for long-run macroeconomic analysis (Nordhaus (1977, 1993)) laid the ground for the validation of a new kind of literature, called *climate finance* (Hong et al., 2020). Climate finance emerged from the interconnections between environmental and financial economics (Giglio et al., 2021a).

Two main currents characterise the literature on climate finance. The first relates to climate change science and the related risks. The second describes the financial consequences of climate change for asset pricing. Climate change risks can be divided into physical and transitional risks (Carney, 2015). Physical risks refer to the mainly negative impact of climate and weather-related events on company operations, society and supply chains (Tankov and Tantet, 2019). There are two types of physical risk: acute and chronic. Acute physical risks are related to *extreme weather events*, such as floods, extreme drought, wildfires, hurricanes and heatwaves. Chronic climate risks represent *slowly* evolving phenomena, such as sea-level rise, changes in precipitation patterns and temperature rise. On the other hand, transitional risks refer to all the possible scenarios coherent with a path to a low-carbon economy and all related implications for fossil fuels and dependent sectors (Curtin et al., 2019). Firm reputation and technology changes represent other transitional risks as well (Semieniuk et al., 2021). This review focuses on both types of climate change risks, and I discuss how their

[5]Notably, several new institutions, organization and initiatives emerged after the Paris Agreement; for instance, the Task Force on Climate-related Financial Disclosures (TFCD) and the Network for Greening the Financial System (NGFS) were both established after the agreement. To understand the overwhelming climate-related regulatory framework in the financial system, Feridun and Gungor (2020) wrote an interesting review with a focus on the banking sector.

dynamics matter for asset pricing.

With respect to the financial side, climate finance literature can be divided according to the type of financial risk and asset analysed, as well as the relative methodology applied. Recent studies have found that climate change could affect different types of financial risks. In particular, studies in climate finance showed that climate change could affect (i) credit (Painter, 2020); (ii) underwriting (NGFS, 2020); (iii) operational and (iv) market risks. In this review, I survey the implications of climate change for market risks. Among several assets whose market value may be exposed to physical risks, such as real estate (Bernstein et al., 2019; Baldauf et al., 2020; Giglio et al., 2021b; Murfin and Spiegel, 2020), municipal bonds (Bourdeau-Brien and Kryzanowski, 2020; Goldsmith-Pinkham et al., 2023; Painter, 2020), and derivatives (Kruttli et al., 2025; Schlenker and Taylor, 2021), in this review, I concentrate on the stock market. However, given the novelty of the field, findings with respect to other asset classes are integrated to foster the comprehension of certain results observed in the literature. Finally, empirical research that focuses on how climate risks are measured in financial portfolios can be divided between top-down and bottom-up approaches. In this review, both methodologies are analysed to review how stock prices interact with climate change dynamics.

In this chapter, I review the literature on climate finance with a focus on the equity market, in order to lay the foundation for the main issues explored in this dissertation. In particular, Section 2.2 discusses the types of data required to analyse how the physical and transition risk channels may influence equity pricing. Sections 2.3 and 2.4 then examine how these risks are modelled using top-down and bottom-up approaches, respectively, and how they affect the cross-section of stock returns. Finally, Section 2.5 concludes by outlining how the empirical chapters of this dissertation contribute to the literature on climate finance.

2.2 Modelling Climate Risks in the Equity Market: The Physical and Transition Risk Channels

This Section reviews how firm value can be affected by either the physical or the transition risk channels. Additionally, I discuss the types of data needed to build measures that proxy for these climate risk drivers and how these measures can be related to firm-level variables. Figure 2.1 presents an overview of the different physical and transition risk drivers as well as the macro-categories of data needed to model climate risks in the equity market.

At the more fundamental level, physical risks depend on the following three drivers (Tankov and Tantet, 2019):

$$\text{Physical risk} = f(\text{hazard, exposure, vulnerability}) \tag{2.1}$$

The variable *hazard* refers to climate events or weather patterns of interest, both in terms of physical intensity and in probability of occurrence. The term *exposure* represents the geographical distribution of the entity or system that the climate hazard might impact, and the variable *vulnerability* refers to the threats (such as fragilities or predispositions) to the asset from of its exposure to the climate hazard. Each term in eq. (2.1) requires specific and geo-spatial data to adapt the analysis to the particular entity of interest.

The term *hazard* in eq. (2.1) can be analysed using two different types of datasets, namely climate and natural disasters datasets. Regarding the former, Tankov and Tantet (2019) classified four different types of climate datasets for modelling physical risks. This classification ranks climate datasets according to the levels of modelling required to create them, distinguishing between (i) observational datasets, (ii) reanalyses datasets, (iii) projections datasets and (iv) climate indices. Observational datasets can be further divided into (i) situ observations (such as weather stations) and (ii) teledection from the ground or from space. In the latter case, the observational dataset is created by means of satellite data. A full review of each these datasets would be beyond the scope of this review. Interested readers are referred to the work of Tankov and Tantet (2019) for a more comprehensive discussion about these climate data. In this work, I describe how these datasets have been used in studies analysing the stock market and the sources to gather these kinds of data.

Although traditionally used in disaster risk management (Doktycz and Abkowitz, 2019), natural disaster datasets are gaining momentum in climate finance. Natural hazards can be divided into (i) hydrological (e.g. floods and mass movements), (ii) meteorological (e.g. storms and tropical cyclones), (iii) climatological (e.g. heatwaves and droughts) and (iv) geophysical (e.g. earthquakes and volcanic eruptions) disasters. Natural disaster datasets are attractive in climate finance because, unlike climate datasets, they provide both the location and the historical economic damages of a certain physical hazard. Notably, the criteria under which a certain natural hazard is accounted for in a specific database may differ across data providers (Doktycz and Abkowitz, 2019).

The quantitative assessment at the firm level of the other two variables in eq. (2.1) requires the use of asset-level data. The latter represents any type of quantitative or qualitative information regarding physical assets, including their characteristics, geographical locations and ownership (Preudhomme and Mazzacurati, 2020). Moreover, the level of a firm's vulnerability to physical risks is negatively related to its adaptation capacity. Thus, modelling this channel further requires data geared toward firm innovation, such as research and development (R&D) expenditures and firm patents.

The choice of a framework to categorise transitional risks is less canonical than the one discussed for physical risks. Nevertheless, Semieniuk et al. (2021) provided a taxonomy that allows one to identify several transition risk drivers that may lead to economic impacts in financial markets. This review describes how the transition risks discussed in Semieniuk et al. (2021) can affect the equity market. Transition risks are a combination of three factors (Semieniuk et al., 2021):

$$\text{Transitional risk} = f(\text{policy risk, technology risk, preference change}) \quad (2.2)$$

The term *policy risk* in eq. (2.2) refers to the risks and opportunities that may be triggered by climate mitigation policies. The aim of these policies is to reduce the amount of greenhouse gas (GHG) emissions in the atmosphere, especially carbon dioxide (CO_2) emissions. The reason for mitigations policies to focus on CO_2 emissions is that these kinds of emissions are considered the primary factor in human-induced global warming (Nordhaus (1977, 1993)). Climate mitigation policies can be implemented via market-based and non-marked-based mechanisms. Market-based mechanisms comprise the two forms of carbon pricing (Metcalf, 2009): (i) carbon taxes and (ii) cap-and-trade schemes. Non-market-based mechanisms are related to (i) environmental regulation; (ii) green subsidies; and (iii) voluntary commitments by government and firms (Bolton and Kacperczyk, 2021b).

The Greenhouse Gas Protocol sets the standards for quantify corporate emissions at the firm level, distinguishing between three different sources of GHG emissions.[6] Scope 1 emissions refer to the direct emissions from plants owned or controlled by a company. Scope 2 and scope 3 emissions represent two forms of indirect emissions. In particular, scope 2 emissions arise from the generation of purchased steam, heat, and electricity consumed by the firm, while scope 3 emissions come from sources not owned or controlled by the company, such as emissions from outsourced activities. Studies in climate finance tend to assume that the higher a company's scope emissions, the

[6] See `https://ghgprotocol.org/`.

'browner' that firm is (Bolton and Kacperczyk, 2021a). The opposite holds for 'green' firms. Moreover, given these sources of scope emissions, three different measures at the plant (Akey and Appel, 2021) or firm level (Hsu et al., 2023) can be derived. The first is the total level of emissions, that may be decomposed for each type of scope emission subcategory. Year-by-year change in emissions quantifies the growth rate in annual corporate emissions. Finally, one could also compute an emission intensity measure, quantifying carbon emissions per unit of sales (Bolton and Kacperczyk, 2021a) or assets (Hsu et al., 2023). Each of these measures can be used to estimate the degree of exposure a company may have to different climate mitigation policies (Bolton and Kacperczyk, 2021a).

The variable *technology risk* in eq. (2.2) refers to the introduction of cost-saving technologies that would foster the adoption of low-carbon energy sources. Notably, society is still reliant on fossil fuel energies, which in 2020 accounted for more than 80% of energy supply (Rapier, 2020). However, several factors may be pushing firms to adopt low-carbon energy sources, such as expected liabilities toward environmental policies (Chu et al., 2020), investor pressure (Azar et al., 2021), or simply to maintain competition in the market (Trinks et al., 2020). Thus, modelling technology risk requires firm-level information about (i) innovation data, such as abatement costs (Akey and Appel, 2021), R&D expenditures, and firm patents aimed to curb firm emissions (Chu et al., 2020); (ii) emission data; and (iii) investor holdings. The latter kind of data allows the researcher to analyse whether corporate governance could affect the carbon management practices of targeted firms. From the motivations that could trigger firms to adopt carbon management practices, it is clear that the variables *policy risk* and *technology risk* in eq. (2.2) are closely interlinked.

Finally, the term *preference change* in eq. (2.2) may be related to two non-mutually exclusive channels (Pástor et al., 2020). The first refers to unexpected preference changes in green-motivated costumers' tastes. This group's environmental concerns may positively affect the cash flows of green firms. The consumer channel may be modelled (i) directly, gathering data from consumer surveys (Ricci and Banterle, 2020) or about firm profitability (Dai et al., 2021); or (ii) indirectly, examining changes in analysts' earnings revisions for green firms (Ramelli et al., 2021). The second channel is represented by unexpected shifts in investor preferences toward carbon-intensive assets. Investors may change their preferences regarding these assets for both pecuniary and nonpecuniary motives. In the former case, the financial logic is tied to risk–return considerations, as carbon assets may be deemed to have a higher downside risk (Ilhan et al., 2021). On the other hand, nonpecuniary motives are related to the ethical benefits an investor derives when holding climate-friendly assets (Fama and French, 2007). Modelling the investor channel requires data about (i) investor surveys (Krueger et al., 2020); or (ii) financial flows toward green labelled funds (Ceccarelli et al., 2019).

Clearly, physical and transitional risks are interlinked. This phenomenon is particularly true for studies attempting to analyse the evolution of *future* physical risk damages, which use projection datasets (Dietz et al., 2016). In these types of analyses, one of the main sources of uncertainty is the future amount of CO_2 concentration in the atmosphere (Tankov and Tantet, 2019). The value of this figure, in turn, will depend upon the effectiveness of climate mitigation policies adopted in the following years (Semieniuk et al., 2021).

2.3 Top-down Approaches: Climate Risks in Investment Portfolios

The aim of this article is to explain how the climate risk drivers described in Section 2.2 should affect the cross-section of stock returns. Analysing how climate risks may systematically affect the equity market pose several modelling challenges for the field of asset pricing. In recent years, however, the climate finance literature has identified two ways to link the dynamics described in eq. (2.1) and (2.2) to equity prices at the top-down level.

According to Giglio et al. (2021a), financial research that models climate risks in macro financial asset pricing models can be divided according to the researcher's beliefs about climate change uncertainty. It remains an open debate whether climate risks represent a low probability outcome resulting in a 'disaster' (Weitzman, 2009) or a stochastic process dependent on today's aggregate consumption (Nordhaus, 1977). One of the main goals of these models is the computation of the social cost of carbon (Bansal et al., 2019; Barnett et al., 2020; Daniel et al., 2016), the value of which has important sociological and policy implications.[7] Although initial estimates of this measure primarily relied on macroeconomic theories, Bansal et al. (2019) and Balvers et al. (2017) argued that the equity market might provide an independent judgment of current future climate change risks. Therefore, empirical evidence on this point can drive climate finance research toward better construction of macro-financial models, and in turn, better estimates of the social cost of carbon.

Other approaches tend to develop theoretical equilibrium models aimed to align environmental, social and corporate governance (ESG) criteria with asset return dynamics (Avramov et al., 2022; Pástor et al., 2020; Pedersen et al., 2020). As discussed in this review, ESG investing is strictly related to climate change considerations by investors (Engle et al., 2020; Pástor et al., 2022). Although some of these models tend to consider the indirect effects that investor preferences toward sustainability may have on asset prices, Pástor et al. (2020) developed a model where climate risks are allowed to determine equilibrium returns, as they enter directly in the investors' utility functions.

[7]The social cost of carbon is a critical ingredient of carbon pricing policies to tackle climate change risks, as it measures the present value of the damage done by emitting an additional ton of CO_2 emissions (Nordhaus, 1977). Different assumptions in macro-financial models may imply different estimations of this measure.

For both of these approaches, the theoretical predictions ultimately rest on how and whether financial markets *price* these risks. The climate finance literature analysing the equity market infers this kind of information through reliance on the results obtained by empirical asset pricing tests of security returns. Thus, in the next subsection, empirical evidence from the application of factor models is reviewed to demonstrate how equity prices are historically related to climate change dynamics.

2.3.1 Factor Models and Climate Change Risks: An Open Debate

Grounded in a solid academic background, factor models provide a general framework to analyse the systematic drivers to explain the cross-section of asset returns. *Linear* factor models represent a special case of the arbitrage pricing theory (Ross, 1976), and assume that the return of an asset can be modelled as a combination of underlying risk factors:

$$r_{t,i} = \alpha_i + \sum_{k=1}^{K} \beta_{k,i} f_{k,t} + \varepsilon_{t,i} \tag{2.3}$$

Suppose factors other than the market portfolio can explain the cross-section of asset returns. In that case, these factors are called *anomalies*, as they are in contradiction with the mean-variance efficiency assumptions of the capital asset pricing model (Sharpe, 1964), and in general, with the (semi-strong) form of efficient market hypothesis (Fama, 1970). Early work in this direction was pioneered by Fama and French (1992) and Fama and French (1993).

Studies in climate finance that employ factor models to analyse the cross-section of stock returns tend to rely on portfolio sorts rather than single stocks, justifying this assumption in light of more stable beta estimations

(Petersen, 2009). Hence, eq. (2.3) becomes

$$r_{t,p} = \alpha_p + \sum_{k=1}^{K} \beta_{p,k} f_{t,k} + \varepsilon_{t,p} \tag{2.4}$$

whose variance, under the assumption of factor models, is defined as

$$\sigma_p^2 = \sum_{k=1}^{K} \beta_{p,k}^2 \sigma_k^2 + \sigma_{\varepsilon,p}^2. \tag{2.5}$$

Thus, reasoning in terms of portfolio, the fundamental debate in climate finance is to understand whether climate change risk dynamics enter in equations (2.4) and (2.5) as parameters α_p, $\beta_{p,k}$ or $\sigma_{\varepsilon,p}^2$. In other words, it is still an open question whether climate risks represent an anomaly, an extra source of market risk priced in the financial market or instead of a firm-specific characteristic that investors could eliminate through diversification. Considered alone, these results make it difficult for a researcher to discern how climate risks should affect equilibrium asset returns.

Given the contradictory results observed in the literature, eq. (2.4) will be assessed sequentially to compare the data, assumptions and empirical results for each study presented more qualitatively. Thus, the discussion begins with the data used to construct the climate risk measures aimed to proxy for the physical and transition risk channels in eqs. (2.1) and (2.2), respectively. I then describe the underlying economic rationale provided by studies in climate finance to link portfolio returns to the climate risk measures. Finally, I discuss the asset pricing implications resulting from empirical evidence of climate risk pricing in the equity market. Table 2.1 summarises the climate risk factors and the economic rationale and the findings for each study presented.

Data and Methods to Construct the Climate Change Risk Proxies

In order to construct the climate risk factor of interest, one needs first to determine the climate risk proxy at the firm or portfolio level. In this subsection, I review the different kinds of datasets and methodologies used to construct proxies of climate risks at the top-down level.

With respect to physical risk measures, Table 2.1 shows the types of measures used to proxy for the term *hazard* in eq. (2.1). Temperature anomalies are the most used variable, with droughts coming in second.[8] The high availability of weather stations worldwide makes this kind of observational data the most natural way to include temperature anomalies in eq. (2.4). Given that this subset of studies in Table 2.1 analysed the US stock market, the data for the temperature time series were mostly retrieved from the U.S. National Climatic Data Center. The temperature beta can be estimated using either the return sensitivity of stocks to the abnormal changes at the monthly (Kumar et al., 2019); annual (Balvers et al., 2017); or quinquennial (Bansal et al., 2019) temperature levels. In the latter case, the aim in Bansal et al. (2019) was to allow the temperature beta to reflect risks related to the economic effects of global warming rather than short-run fluctuations in weather.

Drought measures were proxied by using both climate indices and observational datasets. Regarding the former, climate indices such as the Palmer Drought Severity Index (PDSI) and the Actuaries Climate Index (ACI) are a promising way for tracking over time physical hazards that may not be directly described by a specific climate variable (Tankov and Tantet, 2019). On the other hand, Ding et al. (2020) asserted that satellite data usage provides a more reliable way to quantify such time-series variation, as observational

[8] Temperature anomalies are defined as the difference between the temperature in a particular month and a long-term average temperature for that particular month. The usual value used to compute the average is of 30 years (Kumar et al., 2019). They are more important than actual temperature, given the difficulties in gathering data from some weather stations worldwide.

datasets are less dependent on measurement error problems than climate indices. Nevertheless, the drought risk proxy among these studies tends to be similar, and the approach demonstrated in Hong et al. (2019) is used as a reference in the literature. Specifically, taking the PDSI index as a standard, one may estimate the long-term drought *trend* at a certain location i, up to a certain year t, via the equation

$$PDSI_{i,t} = a_i + b_i t + c_i PDSI_{i,t-1} + \epsilon_{i,t}. \tag{2.6}$$

The parameter of interest in eq. (2.6) is b_i, which can be considered the long-term effect of climate change on a country's drought vulnerability. It is important to understand how the parameter b_i in eq. (2.6) is related to the variables *exposure* and *vulnerability* in eq. (2.1). Generally, studies in climate finance that employ top-down approaches tend to proxy the term exposure in eq. (2.1) using the countries where firm headquarters are located (Jiang and Weng, 2019). However, the facilities of listed firms (such as establishments and branches) may be spread heterogeneously worldwide, and they may feature different levels of profitability within the country where the company headquarters are located (Hugon and Law, 2019). The quality of the above assumption then critically depends on the firm characteristics in the sample under investigation. Hong et al. (2019) found that in most of the countries, the food industries were formed by small to medium-sized enterprises (SMEs). Thus, the profitability of these companies could be more vulnerable to the adverse drought conditions of the country where the company headquarters are located, as these firms would be less likely to geographically diversify their earnings than highly capitalized firms.[9]

Finally, taking a starkly different approach, Nagar and Schoenfeld (2024) constructed a text mining index by counting the number of times the term 'weather' appeared in 10-K company reports of U.S. firms. They refined this

[9]The same argumentation also holds when temperature anomalies or other kinds of hazard are analysed at the firm level.

index by means of part-of-speech tagging techniques. Nagar and Schoenfeld (2024) explained that their index should capture the multi-hazard exposure in eq. (2.1) that a company may experience with different types of physical risks. To the extent that managers are aware of the impacts of weather-related events, Nagar and Schoenfeld (2024) argued that quantitative insights about firm exposure may be extracted by this kind of company (qualitative) information.

On the transition risk side, the studies in Table 2.1 generally construct the transition risk proxies using more homogeneous data sources and methodologies than the ones used to build physical risk measures. Görgen et al. (2020) constructed a score able to proxy for the several transition risk drivers in eq. (2.2). In particular, they developed a 'Brown-Green-Score' (BG) which is defined as

$$\text{BGS}_{i,t} = 0.70 \text{ Value Chain}_{i,t} + 0.15 \text{ Adaptability}_{i,t} + 0.15 \text{ Public Perception}_{i,t} \tag{2.7}$$

The variables Value $\text{Chain}_{i,t}$, $\text{Adaptability}_{i,t}$ and Public $\text{Perception}_{i,t}$ in eq. (2.7) proxies for the terms *policy risk*, *technology risk* and *preference change* in eq. (2.2), respectively.[10] To build the measure, Görgen et al. (2020) relied on 10 different ESG variables, retrieved from four different data providers. Görgen et al. (2020) argued that merging the ESG variables between these datasets should minimise the potential self-reporting bias, an issue that is particularly prominent across ESG providers (Avramov et al., 2022; Berg et al., 2022).

Other studies in Table 2.1 tend to focus on only one of the three firm-level emission variables described in Section 2.2, and researchers often argue that these variables should proxy for the three transition risk drivers in eq. (2.2).

[10] Görgen et al. (2020) explained that the value of the deterministic weights in eq. (2.7) are the results of several workshops held with academics and practitioners.

Hsu et al. (2023) constructed a measure of emission intensity at the firm level by aggregating plant-level data from the Toxic Release Inventory (TRI) database in United States. The Trucost and Thomson Reuteurs' Asset4 ESG databases provide emission data at the aggregated firm level, both for the United States (Ardia et al., 2023; Bolton and Kacperczyk, 2021a; Cheema-Fox et al., 2021; In et al., 2017), and the entire world (Bolton and Kacperczyk, 2020). Moreover, these databases also provide data related to the three different types of scope emissions described in Section 2.2. Bolton and Kacperczyk (2020) and Bolton and Kacperczyk (2021a) decomposed the three measures of carbon risk for each type of scope emission. Notably, as Busch et al. (2018) observed, there is very little variation in the reported scope 1 and 2 two emissions among data providers. This homogeneity in data and methods to build the transition risk proxies should be considered when analysing the differences in empirical results discussed in Subsection 2.3.1.

In conclusion, the remaining of studies in Table 2.1 analysed how both physical and transition risks were priced in the cross section of stock returns. Engle et al. (2020) and Pástor et al. (2022) proxies this overall climate risk exposure by means of the E-scores provided by the MSCI and Sustainalytics databases, arguing that they should capture the different dynamics described in eq. (2.1) and (2.2). Engle et al. (2020) constructed E-score measures at the firm level by taking the difference between positive and negative E-scores subcategories. On the other hand, Pástor et al. (2022) built on the methodology described by Pástor et al. (2020). Furthermore, Gostlow (2019) distinguished between physical and transition risk exposure using asset level data provided by the Four Twenty-Seven (FTS) database. The computation of the climate risk measures provided by this database follows a structure similar to the one presented in eq. (2.7).[11]

[11] For more information, see at: `https://427mt.com/`.

Economic Rationale Underlying the Climate Risk Factors

The true challenge in climate finance studies analysing equity market is to identify the economic rationale that links portfolio returns to climate risk measures. As shown in Table 2.1, the wide spectrum of hypothesis used in this purpose indicated that there is still not a consensus about how the climate risk drivers described in Section 2.2 should affect the cross section of stock returns. In this subsection, I give a detailed review of the assumptions underlying the climate risk factors.

If temperature risk represents a future risk to consumption, companies that are more exposed to long-term risks should provide higher risk premiums to investors today. This is the idea on which the theoretical model by Bansal et al. (2016) is grounded. Bansal et al. (2019) identified these companies as those in the higher decile of portfolios sorted on the book-to-market ratio (Hansen et al., 2008). Building on this idea, Bansal et al. (2019) found that value portfolios with higher dividend betas (i.e. those more exposed to macroeconomic growth risks) dictate monotonic and negative relationships with their temperature betas. Nagar and Schoenfeld (2024) took a simpler approach, showing that their text mining indices can track firm-specific impacts to natural disasters. Specifically, by applying an event study methodology, Nagar and Schoenfeld (2024) showed that firms with the highest text mining index values suffered the worst equity market responses after several hurricane events in the United States.

The economic rationale underlying the transition risk factors can be more thoroughly explained. The portfolio built by Görgen et al. (2020) aimed to mimic the three underlying risk factors in eq. (2.2) in returns. Similar argumentations can be made for the climate risk measures used by Gostlow (2019). For the remaining of studies in Table 2.1, one must understand how the emission variables are related to the cross section of stock returns. As Bolton and Kacperczyk (2021a) argued, the total amount of emissions should proxy for the long-term company's' exposure to transition risks, as it is likely that regulations aimed to curb emissions are targeted more toward these types of firms. The opposite is true for the year-by-year changes in emissions, as this measure should capture the short-term effects of transition risks on stock returns. The economic rationale behind the emission intensity measure is explained using two different channels. Hsu et al. (2023) assumed this measure should proxy for the climate policy risk exposure of pollutant firms, so it is allowed to play a similar role as the total amount of firm emissions as in Bolton and Kacperczyk (2021a). In the works of Bolton and Kacperczyk (2020) and Bolton and Kacperczyk (2021a), emission intensity should be related to the exclusionary screening process applied by institutional investors. In this case, the aim is to test the divestment hypothesis (Hong and Kacperczyk, 2009). This hypothesis would hold if the carbon intensity measure were (i) positively related to stock returns and (ii) negatively related to the holdings of institutional investors. The latter point would be observed in the cross section if carbon-intensive stocks were deemed to be 'sin' stocks by institutional investors (i.e. companies involved in producing alcohol, gaming and tobacco, as explained in Hong and Kacperczyk (2009)). The resultant carbon premium would be then explained by the under-diversification opportunities provided by carbon stocks.

Another strand of studies in Table 2.1 used the economic tracking portfolio methodology to relate portfolio returns to the climate risk measures.[12] If equity prices change according to the arrival of climate change information, one could construct a portfolio of assets that can track news about climate risks. In this way, news can be either (i) a shock in the annual level of temperature (Balvers et al., 2017); or (ii) a text mining index designed to proxy for the arrival of climate change information in financial markets (Ardia et al., 2023; Engle et al., 2020). Economic tracking portfolios can be used to construct either risk factors or hedging portfolios (Lamont, 2001).

[12] In the asset pricing literature, such a methodology is also often referred to as the 'mimicking portfolio approach'.

Balvers et al. (2017) used size and value portfolios as basis assets to construct a temperate risk factor, as these portfolios should have higher levels of vulnerability to temperature shocks. Engle et al. (2020) exploited firms' E-scores to build a hedging portfolio against climate risks. The underlying hypothesis in the work of Engle et al. (2020) is that if green stocks would rise in value when climate information hit financial markets, these stocks would represent a simple asset to dynamically hedge against climate risks.

Pástor et al. (2020) formalised the idea applied by Engle et al. (2020) in a theoretical equilibrium model, where assets are priced by both a market and an ESG (or green) factor. The economic rationale in the Pástor et al. (2020) model is that while green assets have lower *expected* returns because they provide a hedge against climate risks, they could outperform brown stocks if the variable *preference change* in eq. (2.2) shifted unexpectedly. Thus, these unanticipated changes in the consumer and investor demands would then lay the ground for *unexpected* (and positive) returns due to (i) cash-flow news via the consumer channel; (ii) discount-rate news by means of the investor channel; or both (Campbell and Shiller, 1988; Campbell and Vuolteenaho, 2004). Ardia et al. (2023) and Pástor et al. (2022) empirically tested the theoretical predictions of the Pástor et al. (2020) model.

Although the economic rationale underlying the climate measures illustrated above is compelling, a climate risk premium would emerge if market participants correctly *understood* these risks (Andersson et al., 2016). The studies in Table 2.1 employ both a direct and an indirect approach to test market efficiency in pricing climate risks.

The papers analysing the pricing of physical risks began with an indirect assumption. In particular, these studies analysed whether the realisations of physical risk measures in specific countries are informative regarding the profitability of companies that operate in those countries (Hong et al., 2019; Ding et al., 2020). These tests were implemented using either portfolio sorting (Hong et al., 2019) or cross-sectional sorting running Fama and MacBeth

(1973) regressions (Kumar et al., 2019). Again using eq. (2.6) as an example, the portfolios were sorted according to the estimated value of b_i up to a certain year t. Given that lower values of b_i are associated with higher values of drought (when the PDSI index is used), one would expect that the future profitability of firms in the resultant portfolios to be lower (Hong et al., 2019). These tests were applied both in specific industries, as agriculture and related sectors (Ding et al., 2020; Jiang and Weng, 2019; Hong et al., 2019) or across the whole economy (Kumar et al., 2019). The majority of studies in Table 2.1 found that firms' profits can be predicted for time horizons quite long, spanning from one (Ding et al., 2020; Kumar et al., 2019), up to three years (Hong et al., 2019). However, in an efficient market, such a pattern should not forecast stock returns as well, as these portfolio rankings are publicly available. In other words, stock prices should already embed this kind of information (Hong et al., 2019). Unlike the studies analysing physical risks, the works in Table 2.1 assumed that transition risks were underpriced (Cheema-Fox et al., 2021; In et al., 2017) before applying formal asset pricing tests. Given that the methodologies employed to construct risk-adjusted trading strategies are similar for both physical and transition risks, I review both methods in Subsection 2.3.1.

Climate Change Risks in the Cross-Section of Stock Returns

In this final subsection, I explore the mixed evidence about climate risk pricing in the equity market. First, I discuss the implications of studies that found that climate risks are priced. Next, I review the actual debates about the parameters α_p and $\sigma^2_{\varepsilon,p}$ in equations (2.4) and (2.5), respectively.

On the physical risk side, only Bansal et al. (2019), Balvers et al. (2017) and Nagar and Schoenfeld (2024) found that physical risks represent an extra source of market risk priced in financial markets. The conclusions of these studies are important not only for asset pricing but also for policy implications. Specifically, the true aim in Bansal et al. (2019) was to provide a semi-parametric estimate of the social cost of carbon. If the equity market prices temperature risks, then such information is embedded in the estimated temperature elasticity of equity valuations. Using the total global emissions in 2017 as input, they estimated a social cost of carbon of nearly 0.4% of world Gross Domestic Product (GDP). Balvers et al. (2017) found that adding their temperature factor to the Fama and French (1993) factors in eq. (2.4) allows to capture a higher amount of cross-sectional variation in industry-sorted portfolios. Balvers et al. (2017) framed their findings in light of the one-to-one relationship between the cost of capital and GDP per capita growth, as found in Henry (2003). Thus, the result that the cost of equity capital attributed to uncertainty about temperature changes is 0.22% should be viewed in a more broad sense as a (present) value loss of 7.92% of wealth for the US economy. Additionally, Nagar and Schoenfeld (2024) found that the parameter α_p in eq. (2.4) of weather-beta sorted portfolios becomes insignificant once they control for their weather risk factor. In other words, the weather premium proxies for a new type of systematic risk capable of improving the prediction of the cross-section of stock returns in the US. Notably, their results overcame the hurdles set by Harvey et al. (2016), thus mitigating possible data snooping concerns.

Some studies in Table 2.1 found the evidence of a carbon premium in the cross-section. However, it remains unclear which transition risk measure can better explain the carbon premium. Bolton and Kacperczyk (2021a) found that portfolios sorted on the total level and the year-by-year change in emissions were valued at discount. These facts are true regardless of the type of scope emission analysed. Bolton and Kacperczyk (2021a) further showed that the carbon premium is not linked to the emission intensity measure. The findings of Bolton and Kacperczyk (2021a) were echoed by Bolton and Kacperczyk (2020) at the international level, although not all countries are pricing carbon risk to the same extent. Importantly, for both Bolton and

Kacperczyk (2020) and Bolton and Kacperczyk (2021a), the existence of a carbon premium cannot be explained by the divestment hypothesis. Bolton and Kacperczyk (2020) and Bolton and Kacperczyk (2021a) found that institutional holdings seem to be negatively related to the emission intensity measure for some industries, but, again, stock returns are not related to this quantity. On the other hand, Hsu et al. (2023) discovered that the carbon premium is related to the emission intensity measure. However, as revealed by Bolton and Kacperczyk (2020), several robustness tests allowed Hsu et al. (2023) to confute the divestment hypothesis. Hsu et al. (2023) explained the observed premium providing a general equilibrium model and they showed in their model that investors learn from the *signal* of a possible regime change in climate mitigation policies. The different stocks' exposures to such a regime change may explain why investors require a pollution premium in the cross-section of stock returns.

Nevertheless, these findings were not corroborated by the remaining studies in Table 2.1. The tests of market efficiency were implemented using either portfolio sorting (Cheema-Fox et al., 2021; In et al., 2017; Kumar et al., 2019), or cross-sectional sorting (Hong et al., 2019). In the former case, the investment strategy can involve either a trading strategy in the spirit of Jegadeesh and Titman (1993), or the construction of zero-cost portfolios (Kumar et al., 2019). The 'winner' portfolios, when either the physical or the transition risks are analysed, are considered the ones with the lowest sensitivity to the climate risk measure, whereas the opposite is true for the 'loser' portfolios. Regardless of the approach used, however, the portfolios ranked on climate risk sensitivities seem to provide profitable, *risk-adjusted* trading strategies. While not always large in magnitude (Hong et al., 2019; Cheema-Fox et al., 2021), or fading over a short period of time (Kumar et al., 2019), the arbitrage opportunities found in In et al. (2017) and Jiang and Weng (2019) stretched over 10 and 20 years, respectively, indicating that the stock market may effectively underreact to climate risks. The conclusion by In et al.

(2017) and Jiang and Weng (2019) was that climate change represents an extra source of market risk that may not be proxied by traditional factors commonly used in the asset pricing literature, such as market, size, value and momentum.

The empirical findings in Pástor et al. (2022) and Ardia et al. (2023) provided another interpretation for the observed mispricing in studies testing market efficiency, particularly on the transition risk side. Also Ardia et al. (2023) and Pástor et al. (2022) found that a portfolio that is long green stocks and short brown firms exhibits a positive alpha, controlling for other known risk factors in the asset pricing literature. Ardia et al. (2023) and Pástor et al. (2022) showed that such an outperformance is related to both the *preference change* channels in eq. (2.2), and thus to both positive cash-flow and negative discount rate news for green stocks. To further show that such an outperformance is due to unexpected revaluations during the estimation period, Pástor et al. (2022) constructed a counter-factual green factor assuming zero shocks to climate concerns. The striking result in Pástor et al. (2022) was that, in absence of climate news, the green factor performance would be essentially *flat*. Additionally, the findings by Pástor et al. (2022) and Ardia et al. (2023) are coherent with some of the results observed in other studies in in Table 2.1. First, Görgen et al. (2020) found that the nonexistence of a carbon premium is related to an unpriced cash flow change for both brown and green stocks, rather than to the parameter $\sigma^2_{\varepsilon,p}$ in eq. (2.5). Second, their results were also coherent with the positive out-of-sample performance of the hedging portfolio in Engle et al. (2020), given that their portfolio is constructed to have *unexpected* returns with maximum correlation to climate change news.

Importantly, the evidence in Table 2.1 reveals also contradictions in the direction and persistence of the estimated climate risk premia. While studies such as Bolton and Kacperczyk (2020), Bolton and Kacperczyk (2021a) and Hsu et al. (2023) report a positive carbon premium (implying that brown assets earn higher expected returns as compensation for transition risk), others, notably Pástor et al. (2022) and Ardia et al. (2023), identify negative or transient risk premia associated with preference shifts towards green assets. The fact that both effects can coexist suggests that climate risk premia may be time-varying, reflecting the evolving salience of policy, technology and investor sentiment channels rather than a single equilibrium price of risk.

Overall, the contrasting evidence among the studies in Table 2.1 echoes the known issue of the joint tests of the efficient market hypothesis and the risk adjustment procedure (Fama (1970, 1991)). To provide further insights about the mixed evidence described thus far, Table 2.2 shows the number of traditional risk factors employed by each study when testing the climate-sorted portfolios using eq. (2.4).

If the hypothesis advanced by In et al. (2017) and Jiang and Weng (2019) were true, one would expect the priced climate risk factors identified in the studies in Table 2.2 to be orthogonal to other known risk factors in the asset pricing literature. Bansal et al. (2019) did not control for firm-level risk factors but only for consumption growth, arguing that temperature fluctuations should be exogenous to firm-level characteristics. Balvers et al. (2017) regressed the size and value premiums on their temperature risk factor and found that some of the explanatory power of the Fama and French (1993) factors may be related to stocks' exposure to the temperature risks. On the one hand, one could then argue that studies in Table 2.2 testing market efficiency in pricing physical risks that control for these factors should be coherent with the investor irrationality hypothesis. On the other hand, Nagar and Schoenfeld (2024) found that there is a great heterogeneity in the market capitalisation across their weather-sorted portfolios, meaning that physical risk is not a size effect. Thus, the risk premium found by Nagar and Schoenfeld (2024) pointed toward an incorrect risk-adjustment procedure for studies in Table 2.2 analysing physical risk pricing. Similar arguments can be made about the pricing of transition risks (In et al., 2017). However, given that studies analysing green stocks' outperformance tend to construct trading portfolios using similar data and samples when applying asset pricing tests (Ardia et al., 2023; In et al., 2017), it is important to keep in mind that '*high realized returns do not always indicate high expected returns, especially if they are realized over a relatively short period*' (Pástor et al., 2022). Finally, as shown in Table 2.2, the transition risk factors, unlike the physical risk factors, may carry greater quantities of independent information. Although the identified carbon premium is not always orthogonal to other known systematic factors (Hsu et al., 2023), Bolton and Kacperczyk (2021a) found that this premium is robust to the possibility that cash flow news could drive results, meaning that some of the transition risk channels in eq. (2.2) may effectively be priced correctly in the equity market.

To summarise, the empirical evidence presented in this section leaves one with a certain degree of uncertainty in understanding how climate change risks are shaping the form of eq. (2.4), and, in turn, the theoretical predictions of macro-financial models. In particular, is the stock market really inefficient in pricing climate change risks? Are the risk adjustment procedures used in Table 2.2 incorrect? And, if the the answer to the last question is positive, do the risk factors identified in Table 2.2 have a risk-based or a behavioural explanation? In Subsection 2.4.1 and 2.4.2, I address these issues, linking top-down evidence in light of empirical findings resulting from the analyses of bottom-up approaches.

2.4 Bottom-up Approaches: Focus on Firms' and Investors' Characteristics

Bottom-up approaches represent another way the climate finance literature has been used to model the impact of climate change risks in the equity market. The literature in this direction has been ampler, and studies can be divided into the following groups: (i) micro-econometric approaches; (ii) event studies and (iii) surveys. The combined evidence resultant from bottom-up studies is of utmost importance for top-down approaches analysing the equity market. Such evidence could shed light on how the climate risk channels, described in Section 2.2, could determine the cross-sectional variation in stock returns described in the previous section.

The methodology used by **micro-econometric approaches** can be summarised using the following framework. Let $z_{i,j,t}$ be a variable related to a firm i, operating in the industry j, during the fiscal period t. The suffix i can refer to either one of the firm's establishments in the sample (Addoum et al., 2023) or the whole company (Anton, 2021). The suffix t can relate to either fiscal years (Huynh and Xia, 2021), quarters (Addoum et al., 2023), or months (Huynh and Xia, 2021). The variable $z_{i,j,t}$ can represent (i) a measure of operating performance, such as sales growth (Addoum et al., 2020) or return on assets (ROA, Trinks et al. (2020)); (ii) one of the three emission variables discussed in Section 2.2; (iii) a measure of firm's innovation, such as R&D expenses expenses or the number of patents filed by the firm i (Chu et al., 2020); (iv) stock returns, when using a cross-sectional regression (Huynh and Xia, 2021); or (v) a measure of earning forecast surprises (Pankratz et al., 2023a). Studies in climate finance model the impact of climate risks on $z_{i,j,t}$ via the following regression:

$$z_{i,j,t} = \theta + \phi \text{ Climate Risk}_{i,t-k} + X_{i,t-k} + \varepsilon_{i,j,t} \tag{2.8}$$

where θ is a vector meant to capture several types of fixed and time effects at the firm level. The term $X_{i,t-k}$ in eq. (2.8) is a vector of firm-specific control variables, such as market-to-book ratio, firm size and book leverage. Moreover, the subscript k in Climate $\text{Risk}_{i,t-k}$ can be equal to zero according to the specific analysis applied (Bartram et al., 2021). The error term $\varepsilon_{i,j,t}$ is usually clustered at both the firm and year (or other time frequencies) levels (Bolton and Kacperczyk, 2021b), but it can also can also account for *spatial* correlation across errors (Addoum et al., 2020). In climate finance studies analysing physical and transition impacts, the interest in eq. (2.8) is related to the coefficient ϕ of the variable Climate $\text{Risk}_{i,t-k}$. In subsections 2.4.1 and 2.4.2, I explain how such a variable may be related to firm-level variables, along with the asset pricing implications of these findings.

The high data requirements dictated by micro-econometric approaches pushes researchers to utilise more manageable methodologies to see how the financial market reacts to climate-related events. **Event studies** allow to quantify the importance investors attach to the arrival of climate change information. The empirical evidence found in these studies is important for three reasons. First, both types of equilibrium models introduced in Section 2.3 predict that assets more prone to climate change risks should decrease in value when a climate-related shock occurs (Giglio et al., 2021a). Second, event studies reveal the degree to which the equity market anticipated at least part of the climate-related information, in particular on the physical risk side. Griffin et al. (2019) explain well this point:

> '*If investors already price accurately the full range of future weather contingencies (including rare outcomes) in their return expectations conditional on the evidence from extreme weather and climate science, and if they already know that firms are well-adapted to heat [or other] extremes, then one should not expect a biased investor reaction positive or negative to an extreme high surface temperature (EHST) event. Alternatively, (...) should an EHST event correct for an underpricing of physical climate risk, then the new market equilibrium will likely induce a significant and permanent reduction in equity price*'.

Third, and related to the second point, a fundamental issue in event studies is the choice of the factor model to compute benchmark returns. Thus, to provide more evidence regarding the discussion in Section 2.3, I reviewed only studies that took firm characteristics into account when describing abnormal returns around climate-related events.

Finally, **surveys** are another useful tool to answer possible questions that could not be easily addressed by means of tabular (i.e. quantitative) data (CFA, 2020). The surveys presented in this review were conducted on (i) investors (Krueger et al., 2020); (ii) firms (Amel-Zadeh, 2021); and (iii) consumers (Ricci and Banterle, 2020).

Albeit different in nature, the main discriminants behind the observed results provided by bottom-up approaches can be summarised as follows: (i) differences in firm level impacts and (ii) differences in investors behaviour. These two features allow to address directly the anomalies identified in Subsection 2.3.1, and, in particular, the joint tests of risk adjustment technique and efficient market hypothesis. Specifically, the possibility of new firm-level measures to keep into account in constructing factor models or investor behavioural biases toward climate change risks is analysed in 2.4.1 and 2.4.2, respectively.

2.4.1 Firm Level Impacts of Climate Change Risks

One important point from the discussion in Section 2.3 is that one must understand how firm-level characteristics are related to the climate risk drivers described in Section 2.2. Empirical answers to this issue are crucial for several reasons. First, understanding the economic and financial channels driving firm exposure to climate shocks could foster the construction of a measure aimed to build tradable risk factors. If climate-exposed stocks are subject to common shocks, there will be a common variation in the returns of companies with similar levels of this climate risk measure. Second, whether these risk factors should represent a new type of systematic risk strictly depends on empirical evidence regarding the systematic impacts of climate shocks on firms. Third, it is also important to investigate whether the risk factors widely used in asset pricing literature may *proxy* for these exposures (such as value and size premium, as found in Balvers et al. (2017)). The last point still represents an interesting open question, as will be discussed in this and the next section.

Given the different types of datasets and methodologies reviewed in this review, I described how studies in climate finance used to model physical and transition impacts at the firm level in subsections 2.4.1 and 2.4.1, respectively. Additionally, I describe the possible inferential issues in using one econometric specification over another, particularly on the physical risk side. Finally, I discuss whether the documented impacts should be deemed systematic or not and the implications of these findings at the top-down level. Table 2.3 summarises the results of studies on climate finance analysing climate risks at the firm level.

The Effects of Climate and Natural Hazards on Listed Firms

When modelling physical risks, the variable Climate $\text{Risk}_{i,t-k}$ in eq. (2.8) can assume different forms depending on the specific *hazard* in eq. (2.1) the researcher is analysing. If she wants to model temperature and precipitation risks on $z_{i,j,t}$, then Climate $\text{Risk}_{i,t-k}$ can be either (i) the level of temperature or precipitation averaged over a certain period of time (Anton, 2021) or (ii) the number of days during the month that the levels of temperature or precipitation exceed or fall below certain thresholds (Pankratz et al., 2023a). The term Climate $\text{Risk}_{i,t-k}$ is also allowed to take more complex forms if temperature risk is modelled, allowing for non-linear impacts on $z_{i,j,t}$ (Addoum et al., 2023). If a natural disaster is analysed, then Climate $\text{Risk}_{i,t-k}$ is usually a dummy variable taking the value of one if a certain hazard hit the city (Pankratz et al., 2023a) or the county (Huynh and Xia, 2021) where the establishments of firms are located. When analysing physical risks at the firm level, eq. (2.8) can estimated using either (i) a panel regression (Addoum et al., 2020; Huynh and Xia, 2021); (ii) a quantile regression (Anton, 2021); (iii) a spatial econometric (Lucas and Mendes-Da-Silva, 2018); or (iv) a difference-in-difference (DID) estimation framework (Alok et al., 2020).

As discussed in Section 2.2, modelling the impacts of climate and natural disasters at the firm level requires different types of datasets. In general, micro-econometric approaches analysing temperature and precipitation risks tend to prefer reanalysis datasets because they provide greater spatial-temporal coverage than observational datasets.[13] If the analysis is conducted in the United States, the PRISM dataset is generally used (Addoum et al., 2020, 2023). On the other hand, the European Centre for Medium-Range Weather Forecast's ERA5 dataset has been employed in international settings (Pankratz et al., 2023a; Pankratz and Schiller, 2024). With respect to natural disaster datasets, both the Emergency Events Database (Pankratz and Schiller, 2024), and the Spatial Hazard Events and Losses Databases of the United States (Alok et al., 2020; Huynh and Xia, 2021) have been used to gather data about disaster losses at the national or regional levels, respectively. To account for firms' locations in the United States, the National Establishment Time-Series (NETS) provides sales and other kinds of metadata (e.g., addresses) for each U.S. establishment owned by each public firm (Addoum et al., 2020). At the international level, the Orbis database can be used to retrieve data regarding sales and addresses of firm headquarters and their establishments (Pankratz and Schiller, 2024). However, in Orbis the financial accounting variables are not always available for firm branches. Thus, Pankratz and Schiller (2024) limited their analysis to only SMEs, assuming these firms to be less geographically diversified (as in Hong et al. (2019)). Notably, any of the studies in Table 2.3 made use of innovation data to construct $z_{i,j,t}$ in eq. (2.8). Studies in climate finance analysing physical impacts at the firm level infer the firm's adaptation capacity through analysing specific variables of the income statements. Thus, if a certain accounting variable in the bottom line of the income statements (e.g., firm's

[13]Reanalysis datasets allow one to capture the spatial-temporal value of a certain meteorological variable within a certain grid. However, given that the meteorological variables are estimated across grids, one must remember that the resultant measurement error will depend on the data assimilation system used to construct the reanalysis dataset (Tankov and Tantet, 2019).

earnings) is negatively affected by physical risks, then it is likely that these effects are net of firm's hedging activities (Addoum et al., 2023).

Once eq. (2.8) is estimated at the firm or establishment level, studies in climate finance analysing physical risks at the firm level generally proceed as follows. First, these studies analyse the statistical significance of the coefficient ϕ in eq. (2.8). Second, they may (Addoum et al., 2023; Huynh and Xia, 2021), or may not (Anton, 2021) analyse how market participants react to these impacts. In this subsection, I review the first set of results, and I analyse equity market responses in Subsection 2.4.2.[14]

Some studies in environmental economics have concluded that the negative effects of climate hazards mainly affect developing economies (Dell et al., 2012; Hsiang, 2010). These works have focused on the impacts on macroeconomic aggregates such as GDP, and it is only recently that researchers in corporate finance have begun to explore the implications of climate hazards at the firm level. For instance, Rao et al. (2021) analysed the impact of the monsoon season on the Indian firms' investment processes. They found that firms more exposed to extreme rainfall conditions increased their levels of capital expenditures and that such a pattern tends to persist for up to three years after extreme precipitation. Nevertheless, climate hazards may have *both* positive and negative impact on firm level outcomes. Lucas and Mendes-Da-Silva (2018) documented extreme temperatures, and rainfall positively impacted the performance of Brazilian energy firms, consistent with the increase in energy consumption during these months.

Merging the PRISM and NETS databases, Addoum et al. (2020) found that, on average, neither sales nor productivity growth rates were impacted by extreme temperature levels among the populations of establishments and firms in United States. Addoum et al. (2020) concluded that their results were driven by the fact that the American listed firms have greater resources

[14] This also explains why some studies analysing physical risks at the bottom-up level can be found both in Table 2.3 and Table 2.4.

to adapt to extreme weather conditions than companies in developing countries. However, different econometric settings when estimating eq. (2.8) may have starkly effects on final inferences. In a subsequent paper, Addoum et al. (2023) found that when $z_{i,j,t}$ was aggregated at the industry-by-season level, quarterly earnings could be predicted in over 40% of US sectors (using the Global Industry Classification Standard, or GIC, six-digit code). More important is the fact that this kind of relationship is not only (i) bi-directional (as shown by Lucas and Mendes-Da-Silva (2018)); (ii) spatial and (iii) seasonal dependent, but it is also *non*-linear, a pattern well-documented in the environmental economics literature (Tol, 2009). Addoum et al. (2023) analysed what could determine such a sensitivity to extreme temperature risks. They showed that the demand (rather than supply) channel implied lower revenues for the affected sectors, an outcome explained by the effects that extreme temperature may have on consumers' behaviour (Graff Zivin and Neidell, 2014). Similar outcomes emerged from a recent survey by Amel-Zadeh (2021), who found that firms are worried about the effects of physical risks on consumer demand.

The effects on firm sales found in Addoum et al. (2023) have been echoed in a series of similar works. For instance, Hugon and Law (2019) and Pankratz et al. (2023a) showed that firms headquartered in areas with higher regional temperature variations exhibit decreases in earnings during extreme hot periods. Notably, Hugon and Law (2019) found that larger (in terms of market capitalisation) and more geographically diversified firms do not exhibit the same negative effects (affirming the results by Balvers et al. (2017)). However, the empirical evidence about the economic channels driving the temperature impacts on firms' sales differed across studies. Whereas Anton (2021) and Pankratz et al. (2023a) corroborated the evidence about the demand channel revealed by Addoum et al. (2023), Hugon and Law (2019) found that the supply channel was driving their results, particularly via an increase in operating expenses. In a recent paper, Pankratz and Schiller

(2024) also found support for the supply channel. Using an international sample, Pankratz and Schiller (2024) showed how the negative effects of extreme temperatures and floods on suppliers could cause negative operating performances of their corporate customers.

The econometric setting is also relevant when eq. (2.8) is estimated analysing the impact of natural disasters at the firm level. For instance, Dessaint and Matray (2017) found a statistically insignificant difference between sales growth of firms headquartered in affected counties and that of nearby firms. However, when the locations of firms were identified by considering all the firms' establishments in other counties, Huynh and Xia (2021) found that multiple climate hazards had an impact on overall firms' growth sales.

Overall, the combined evidence of micro-econometric approaches analysing physical impacts at the firm level leads the following conclusions. First, physical risks should neither be thought to belong only to agricultural or related sectors (Addoum et al., 2023) nor be limited to only temperature risks (Huynh and Xia, 2021). Second, because physical risks may impact both the supply and demand channels in different parts of the world (Pankratz and Schiller, 2024), it is likely that several companies in several sectors are exposed to various degrees to physical risks. Taken together, these results would justify the emergence of a systematic physical risk premium in the cross section of stock return. The text mining measure used by Nagar and Schoenfeld (2024), although not complex in nature, may proxy for these multi-hazard exposures. However, little can be said regarding firms' adaptations to these risks. Taking the Nagar and Schoenfeld (2024) measure as an example, two firms with the same value of the text mining index may have two different types of innovation strategies to adapt to physical risks. Thus, modelling such an adaptation channel at the firm level is a promising avenue for future studies on climate finance.

Firms' Responses to Transition Risks and Consumers' Behaviour

As with physical risks, the variable Climate $\text{Risk}_{i,t-k}$ in eq. (2.8) depends on the specific transition risk driver the researcher is designed to model at the firm level. Thus, there are three different ways to model the transition risks described in eq. (2.2) by means of eq. (2.8). When modelling *policy risk*, Climate $\text{Risk}_{i,t-k}$ is referred to a specific climate mitigation policy, which may be a market (Bartram et al., 2021) or a non-market-based mechanism (Akey and Appel, 2021). When modelling *technology risk*, the variable Climate $\text{Risk}_{i,t-k}$ may again coincide with a specific climate mitigation policy, but also with (i) a measure of carbon efficiency (Trinks et al., 2020); or (ii) the fraction of shares of firm i held by an institutional investor during a specific fiscal period (Azar et al., 2021), in order to see whether investor pressure trigger firm carbon management practices. The effects of the investor channel of firm level outcomes are analysed in Subsection 2.4.2. Finally, if the consumer channel is analysed at the firm level, then Climate $\text{Risk}_{i,t-k}$ can represent either (i) the percentage of green-motivated costumers toward firm i (Dai et al., 2021) or (ii) quantitative results obtained from consumer surveys (Ricci and Banterle, 2020). On the policy and technology risk side, *quasi*-experimental studies are often employed by researchers to ascertain the causal effects that policy and external shocks have on $z_{i,j,t}$ in eq. (2.8). Exploiting the fact that these shocks are local, studies in climate finance tend to infer the causal effects of Climate $\text{Risk}_{i,t-k}$ on $z_{i,j,t}$ via a DID (Akey and Appel, 2021) or a a triple-DID (Bartram et al., 2021) estimation framework. Nevertheless, in specific analysis, panel regression can also be used when transition risks are modelled using micro-econometric approaches (Trinks et al., 2020; Xu and Kim, 2021).

Given the multiple forms the variables $z_{i,j,t}$ and Climate $\text{Risk}_{i,t-k}$ can take in eq. (2.8) when transitional risks are analysed, several types of datasets may be used. Plant level emissions in the US can be gathered using the

TRI (Xu and Kim, 2021) or the Facility Level Information on GHGs Tool (Bartram et al., 2021) datasets. With respect to firm innovation, Thomson Reuters DataStream provides R&D expenditures at the national and international level, respectively, whereas firm patents can be gathered by the National Bureau of Economic Research patent databases for the United States (Chu et al., 2020). When analysing climate mitigation policy shocks, the dataset for the variable Climate $\text{Risk}_{i,t-k}$ in eq. (2.8) is generally constructed by the researcher (Akey and Appel, 2021). Investor holdings data are generally retrieved from the 13F Thomson Reuters or FactSet databases (Azar et al., 2021). Finally, data about the consumer channel can be retrieved directly from consumer surveys (Ricci and Banterle, 2020), or from Compustat, which provides the amount of consumer expenditures toward firm i for the United States (Dai et al., 2021).

Studies analysing the effects of policy risk are mainly interested in exploring how firm-level emissions vary according to the environmental regulation employed in a specific state (Bartram et al., 2021), or country (Ben-David et al., 2018). If environmental policies prove effective, one would expect that firms in the treatment group (i.e. the ones located in the state or country where the policy was applied) to exhibit lower levels of emissions, operating performance or both. Nevertheless, the majority of studies in Table 2.3 revealed that the regulatory arbitrage of firms allowed them to systematically overcome the effects of the policy measure, both at the state (Akey and Appel, 2021; Bartram et al., 2021; Xu and Kim, 2021) and country levels (Ben-David et al., 2018). Notably, these aggressive corporate environmental policies seem to be linked to certain firm-level characteristics. In particular, financially constrained firms relocated their emissions in other locations after the introduction of the California cap-and-trade program in 2013 (Bartram et al., 2021) and where probability of having environmental liabilities is low (Xu and Kim, 2021). Moreover, in some cases there is no evidence that these policy measures have affected the profitability of constrained firms (Bartram et al., 2021). These results may explain why the survey by Amel-Zadeh (2021) found that at the international level, firms have been ranking climate policy risks as less important than physical risks.

On the technology risk side, the results of micro-econometric approaches in Table 2.3 corroborate some of the outcomes found in Section 2.3. As Görgen et al. (2020) argued, their transition risk factor is unpriced because green firms are becoming greener than brown firm faster. Görgen et al. (2020) further explained that their risk factor is unpriced because its unanticipated changes are related to unexpected revaluations when both brown and green stocks surprise the market by adopting low-carbon strategies. Bolton and Kacperczyk (2021b) analysed firm commitments to reduce their carbon emissions worldwide. They found that the reduction in emissions mainly arose from commitments from greener firms, meaning those with fewer emissions. Furthermore, Trinks et al. (2020) demonstrated that at the international level, firms with higher levels of carbon efficiency (i.e. those with higher values of the ratio of target-to-actual carbon emissions relative to their peers) tend to have higher ROA and higher market valuations.

Also brown firms are acting to some extent to reduce their carbon exposure. Chu et al. (2020) documented that firms decrease their toxic emissions when their headquarters are located near places where environmental spills have recently occurred. Chu et al. (2020) explained this outcome in light of firms aiming to adapt to possible future environmental liabilities. Lv and Bai (2021) analysed how Chinese firms had responded to the introduction of the China's Carbon Emission Trading Mechanism. They showed that firms generally increased their R&D expenditures and that the market rewarded these companies with higher valuations. However, firm financial frictions seem to be major barriers to corporate innovation policies. For instance, De Haas et al. (2021) showed that firms with higher financial constraints operating in emerging economies tended to avoid carbon reduction plans in recent years. Xu and Kim (2021) explained how financial constraints may affect corporate environmental policies as follows:

> '*The optimal environmental abatement expenditures presuppose that the marginal cost of abatement equals the marginal reduction in expected legal liabilities. (...) As financial constraints unveil and drive up the cost of financing, the marginal cost of environmental abatement increases correspondingly. Holding other factors constant, financial constraints reduce firms' abatement activities and consequently increase total toxic releases.*'

Finally, the direct impact of the consumer channel on firms' financial outcomes has received little attention in the climate finance literature. This is unexpected for two reasons. First, as shown in eq. (2.7), public concerns are given the same weight as firms' adaptability to a low-carbon economy. Moreover, recent studies in asset pricing emphasise how the relevance of firms' consumer capital may be reflected in the cross section of stock returns (Dai et al., 2020; Dou et al., 2021). The only notable exception can be found in the work by Dai et al. (2021) and Ricci and Banterle (2020). Dai et al. (2021) demonstrated that firms supplying their products to green corporate consumers are less prone to relocating their quantities of scope 3 emissions to other countries. Ricci and Banterle (2020) surveyed Italian retail consumers and found that they shifted their purchasing behaviours toward green products after the Paris Agreement, in line with the prediction of the Pástor et al. (2020) model.

The impacts of transition risks at the firm level lead the following conclusions. First, certain studies have documented how historically the regulatory arbitrage of firms may mitigate the effects of climate policy risks, obscuring the possibility that policy risk is priced in the equity market. However, equities prices represent forward-thinking expectations about the cash flows of a firm. Investors' expectations about the effects of policies aimed to curb emissions nationally and worldwide may still make available a transition premium in the equity market. Having said that, these studies provide compelling evidence of how non-coordinated regulatory solutions may systematically distort investors' beliefs, in turn lowering the demand of a carbon premium in some countries, as reported by Bolton and Kacperczyk (2020). Second, firm financial constraints seem to be a relevant financial channel hindering firms' capabilities to adapt to a low-carbon economy, both in developed (Bartram et al., 2021) and developing countries (De Haas et al., 2021). On the one hand, Hsu et al. (2023) found that the carbon premium cannot be explained by financial constraints of firms, thus reinforcing the policy risk channel in United States. On the other hand, financial constraints may represent a relevant financial friction driving firm exposure to low-carbon technology risks in the long run. Therefore, integrating these considerations when developing the equilibrium models introduced in Section 2.3 would be a valuable avenue for future studies in climate finance. Additionally, future research is needed to investigate the direct effects that consumers may have on the cash flows of carbon intensive firms, given the non-negligible role that this channel plays in some of the models introduced in Section 2.3 (Pástor et al., 2020; Pedersen et al., 2020).

2.4.2 Investors' Beliefs About Climate Change Risks: Sentimental or Fundamental?

A critical issue arising in Section 2.3.1 referred to the concerns of possible stock market inefficiency in pricing climate change risks, a result in accordance with recent theoretical works (Thomä and Chenet, 2017). Nevertheless, these studies contrast empirical works showing that climate risks are priced in the cross section of stock returns (Hsu et al., 2023; Nagar and Schoenfeld, 2024). Thus, to provide more quantitative insights about how the stock market interacts with climate risks, it is crucial to answer the following questions:

- *Do* investors price climate-related risks in the equity market on an ex-ante or ex-post basis?

- *How* do investors utilise climate-related information?

- *When* did investors begin to analyse these kinds of data?

This subsection reviews the findings of the climate finance literature with respect to each of these questions, combining all of the empirical evidence provided by bottom-up approaches. Moreover, the focus here is not only on investors' behaviour but also on the different types of investors, given the heterogeneous effects they may exert on firm-level outcomes (Azar et al., 2021). Table 2.4 summarises the findings for studies analysing how investors are interacting with climate change risks in the equity market.

When Do Climate Change Risks Enter in Stock Prices?

The evidence provided in Section 2.4.1 has shown that climate-related events should represent a concern for investors in financial markets. If investors would correctly identify firms' exposure to climate risks in their return expectations (i.e. on an ex-ante basis), expected returns would be a good proxy of realised returns. In particular, investors' hedging demand for climate risks would allow the researcher to estimate the resulting climate risk premium in the cross-section of stock returns.

One of the main sources of investors' return expectations may be related to the valuation of sell-side analysts disseminating company information (Huynh et al., 2020). However, most studies have found that analysts may not drive a fair assessment of climate risks at the firm level. This fact may be one of the reasons why investors tend not to correctly price their portfolios' exposure on an ex-ante basis, particularly on the physical risk side.[15] On the one hand, Addoum et al. (2023) documented that some sell-side analysts consider the effects of extreme temperature in their quarterly

[15] I describe other possible explanations in Subsection 2.4.2.

valuations in the United States. On the other hand, Pankratz et al. (2023a) showed that the opposite is true in an international sample. In particular, Pankratz et al. (2023a) found that an increase in earnings deteriorations by firms due to extreme temperatures was systematically followed by negative performance analysts' surprises. Moreover, a number of studies revealed that the implied cost of capital (i.e. a proxy for expected returns, whose value is strictly dependent on analysts' evaluation models, according to Pástor et al. (2008)) is correctly priced for physical (Huynh et al., 2020) and transition risks (Chava, 2014). Nevertheless, these works cannot explain the number of anomalies documented in Table 2.1. In particular, the implied cost of capital focuses only on the ex-ante level of discount rates rather than on dynamic changes therein (Pástor et al., 2022). Specifically, when the climate risk premium is estimated over short-estimation periods, expected returns may differ from realised returns if unexpected news affects the equity market. The way in which the market responds to unanticipated climate events (i.e. climate risks are priced ex-post) may affect substantially the performance of the climate risk factor.

To analyse ex-post market responses to climate-related information studies in climate finance used both micro-econometric approaches and event studies. Clearly, the interest in event studies analysing transition news differs from the interest in studies examining physical news. In the former case, studies in climate finance generally explore the equity responses at the industry level and whether green firms increase in value during specific realisations of transition risks. In the latter case, event studies focused more on whether certain firm characteristics may drive ex-ante investors' expectations toward firms' vulnerability to these risks (Griffin et al., 2019).

With respect to transition risks, the empirical results by event studies confirmed some of the results found in Ardia et al. (2023) and Pástor et al. (2022). In particular, Ramelli et al. (2021) documented that after the 2016 presidential election of Donald Trump, a staunch supporter of the U.S. carbon industry, firms with higher ESG scores increased in value. Given that analysts' forecasts for these firms had not risen (i.e. the cash flow news hypothesis would not hold), Ramelli et al. (2021) concluded that this result was in line with the fact that climate-friendly stocks would have provided a hedge against unexpected policy shocks in coming years (supporting the discount rate news hypothesis). In a related study, El Ouadghiri et al. (2021) documented that during periods of increased public attention to environmental issues, standard indices with a higher carbon exposure underperformed more sustainable ones. Moreover, Diaz-Rainey et al. (2021) found that the announced withdrawal of the U.S. from the Paris Agreement negatively affected the oil and gas sector in the United States. This effect was consistent with the fact that investors had been gradually expecting future environmental liabilities for these companies, regardless of the actual effectiveness of climate mitigation policies. Notably, the above studies tend to focus on the U.S. market only. It would be valuable to analyse whether the documented excess returns would be lower in magnitude if one controlled for the priced transition risk factors found in Bolton and Kacperczyk (2021a) and Hsu et al. (2023).

As discussed in Section 2.2, physical risks are multidimensional (Pescaroli and Alexander, 2018; Tankov and Tantet, 2019), and thus several event studies have focused their attention only on a subset of specific climate-related events. For instance, Bourdeau-Brien and Kryzanowski (2017) analysed the impact of different natural disasters on equity returns in the U.S. market. Their work introduced the idea that a large ex-post event window is needed to measure the equity market response, as it takes some time to provide reliable estimates of the economic damages of the particular climate hazard of interest. Bourdeau-Brien and Kryzanowski (2017) found that while no reaction appeared in the short term, the stock market reacted positively and negatively after two to three months, but only for a small number of natural disasters. Nevertheless, they showed that neither the industry classification nor the firm size could explain the sign of abnormal returns at any event period length. On the other hand, Griffin et al. (2019) found that excess returns around EHST days are lower in magnitude if one takes into account the size and value premium, arguing that these two factors *may* proxy for market expectations about climate-related risks (thus confirming again the results found by Balvers et al. (2017) discussed in Section 2.3.1). However, these concerns were directly addressed by Lanfear et al. (2019), who examined whether natural disaster, in particular, hurricanes, could explain part of the size and value anomalies. They documented that small firms and growth stocks have been affected significantly *after* the realisation of these extreme events, although the most important outcome is the deterioration in stocks' liquidity. A similar result was found by Rehse et al. (2019), who showed the uncertainty effects generated by Hurricane Sandy on the real estate investment trusts market in the US. This finding reinforces the outcomes from Lanfear et al. (2019), who noted that '*risk-based explanations may not be sufficient and some sentiment-related factor is likely to be an important component for understanding our findings*'.

Supporting the hypothesis proposed by Lanfear et al. (2019), the evidence about micro-econometric approaches can be summarised by explaining that the ex-post reactions to physical risks in the stock market have been documented to be both undue (overreaction) and belated (underreaction).[16] In particular, the literature revealed that such a response is somewhat dependent on the personal traits well-documented in the behavioural finance literature (Bassi et al., 2013); what emerges is that market responses to physical risks are driven by both salience and local biases. Importantly, the behavioural evidence surveyed here also helps to explain the conflicting empirical results on climate risk premia reported in section 2.3.1. Underreaction and salience biases (Dessaint and Matray, 2017; Alok et al., 2020) imply

[16] The evidence of investors' behavioural biases toward climate change risks have been analysed only with respect to the realisations of physical impacts. The only exception can be found in the work of Benz et al. (2020), who showed how institutional investors tend to herd with respect to their decarbonization strategies.

temporarily positive premia for green assets as markets correct prior underpricing, whereas increasing awareness and policy anticipation can compress those premia, turning them negative once climate risks become fully priced. This perspective may therefore reinforce the notion of a non-stationary or regime-dependent climate premium rather than a fixed positive or negative coefficient.

Using international data, Choi et al. (2020) found that retail investors exposed to unusual and local high temperatures (i.e. a salient event that proxies but does *not* represent climate change) tend to buy low carbon stocks and, at the same time, sell high carbon stocks. Given that no evidence of price reversal is observed in the subsequent months, Choi et al. (2020) concluded that this patter would be in line with a slow belief updating in climate change risks. Donadelli et al. (2020) analysed how the equity market responds to tornado activity in the US. They found that equity responses are (i) bi-directional; (ii) industry-specific; (iii) local (in the sense that investors penalised more firms with the headquarters near to the occurrence of these kinds of events) and (iv) lagged (as in Bourdeau-Brien and Kryzanowski (2017)). This sluggish market response in pricing physical risks would justify the presence, even if temporary, of risk adjusted trading opportunities as identified by Hong et al. (2019) and Kumar et al. (2019).

As regards to overreaction, Alok et al. (2020) documented that fund managers tend to overreact to acute physical risks, as the affected firms sold by managers tend to outperform less exposed ones in the two years following a climate disaster. Huynh and Xia (2021) extended the results of Alok et al. (2020) to the entire population of U.S. investors, providing a possible behavioural explanation for the premium identified in Nagar and Schoenfeld (2024). In fact, Huynh and Xia (2021) found that the overreaction of investors could explain why firms more exposed to natural disasters may *outperform* less exposed ones. In particular, Huynh and Xia (2021) showed that investors' overreactions depressed current stock prices, causing future returns to be higher. The overreaction hypothesis was further confirmed given that Huynh and Xia (2021) found, as discussed in Section 2.4.1, that that the fundamentals of affected firms deteriorated after the disasters. Notably, greener firms, although they suffered similar losses in sales after disasters, were the ones that suffered the lowest selling pressures.

There are several implications of observed results in this subsection for top-down approaches. First, these results suggest that the economic tracking portfolio proposed by Lamont (2001) may be useful for addressing the fact that the market tends to misprice physical risks. In fact, as Lamont (2001) explained:

> '*(...) suppose that asset markets are inefficient, irrational sentiment affects market prices, and returns are partially predictable. In this case, as long as asset prices reflect some information about future economic variables, tracking portfolio returns will still be useful for hedging and forecasting'*.

Moreover, it seems that green assets tend to empirically pay off in times of negative climate change realisations. Here, the phrase 'negative climate change realisations' is intended in a broad sense, as the studies presented above showed that investors demand green assets both after extreme weather events (Choi et al., 2020; Huynh and Xia, 2021), and uncertain policy shocks (Ramelli et al., 2021). Together, these results may not only explain the superior performance of green strategies found in Table 2.1 but also justify a negative climate beta toward climate risk factors for green stocks. These results were assumed in the theoretical model proposed by Pástor et al. (2020). I discuss the implications for expected returns of these patterns in Subsection 2.4.2.

Investors' Engagement and the Value of Climate Risks Disclosure

Once the way investors respond to these kinds of events is acknowledged, it is important to understand how they tend to process climate-related information. Investor surveys provide compelling evidence on this point. The Chartered Financial Analyst Istitute CFA (2020) found that 60% of portfolio managers do *not* incorporate climate risks in their analysis. The main barriers for investors are both the little knowledge of climate risk integration in the investment process (Bouchet et al., 2021) and a lack of disclosure from firms, which does not allow investors to develop proper measurement tools. The same results were also found by Amel-Zadeh (2021) and Krueger et al. (2020), thus indicating that investors are '*still learning how to deal with these risks*' (Krueger et al., 2020). In spite of these issues, investor surveys seem to indicate that in recent years investors have been actively *engaging* with firms to manage their portfolios' climate change exposure.

Consistent with Pástor et al. (2020), investor surveys have shown that there may be both financial and nonfinancial reasons why investors would like to decarbonise their portfolios. The main financial reason for institutional investors seems to be the protection of their reputations (Krueger et al., 2020), which in turn may attract investment clients particularly concerned with environmental aspects (Ceccarelli et al., 2019). This result reflected what studies at the bottom-up level found. Not only mutual funds (Azar et al., 2021), but also hedge funds (Akey and Appel, 2019; Chu and Zhao, 2019) have been cooperating with firms to develop corporate policies to lower the emissions of targeted companies. The final goal for investors is reducing the carbon footprints of their portfolios. These results align with those of Shive and Forster (2020), who found that firms tend to emit less when mutual fund ownership is higher. Moreover, although these sustainable campaigns require a significant amount of financial resources to influence the target firm (Dimson et al., 2021) and the rate of their successful completion is generally low, investor surveys have revealed that few investors divested if not satisfied with firms' responses (CFA, 2020; Krueger et al., 2020). In fact, divestment may have detrimental effects, particularly for large passive investors (Azar et al., 2021), and this strategy may not always lead to the desired effects in target companies (Davies and Van Wesep, 2018).

The fact that investors pay particular attention to their portfolio's carbon footprint has two important implications. First, the above results seem to empirically rule out the divestment hypothesis, discussed in Section 2.3. This is important because confuting this hypothesis implies that investors are systematically pricing carbon risk at the *firm* level (Hsu et al., 2023). In other words, investors are recognising that industry (Bolton and Kacperczyk, 2021a), and international diversification (Bolton and Kacperczyk, 2020), may not be sufficient when analysing carbon risk. Second, the results from above studies also emphasise the relevance of corporate governance as a parallel instrument to climate mitigation policies. In particular, investors' pressure on targeted companies may decrease the possibility of firms' regulatory arbitrage practices discussed in Subsection 2.4.1.

Furthermore, investors have also been engaging with firms to increase the amount and quality of climate-related information (Flammer et al., 2021). In fact, in the investor surveys by Ilhan et al. (2023b) and Krueger et al. (2020) it is recognised that some kind of *underpricing* may be present in the equity market, as some studies in Section 2.3.1 confirmed (Hong et al., 2019). Additionally, institutional investors think that climate reporting may be the most effective way to increase market efficiency in pricing physical and transition risks (Ilhan et al., 2023b), ultimately increasing firm value, as empirically shown by Flammer et al. (2021) and Krueger (2015). However, these results should be compared with a survey conducted by Amel-Zadeh (2021), who discovered that, despite the fact that climate risks had a material impact on business operations, firms deliberately chose *not* to report climate risk information in their annual disclosure reports. In particular, this kind of information could result in proprietary costs for a company (Ilhan et al., 2023b).

This kind of empirical evidence has policy implications, such as in the need of a mandatory and standardised reporting set by the Task Force on Climate-related Financial Disclosures. However, this evidence should also be aligned with the theoretical debates in asset pricing literature. In a recent paper, Barahona et al. (2021) argued that in the extreme cases where investors cannot predict the future beta (i.e. the exposure) with respect to a certain risk factor, the resultant risk premium would be lower. They explained such a hypothesis because the impossibility to acquire such a factor loading will, in turn, render the formation of beliefs about an ex-ante risk premium difficult, thus lowering the hedging demand for that factor. Their work is in line with the study by Barnett et al. (2020) and Bourdeau-Brien and Kryzanowski (2020) and with the general idea that *ambiguity* (rather than *risk*) aversion, may shape the behaviour of investors toward climate change risks.

The argumentations made by Barahona et al. (2021) are of particular relevance for investors' expectations about physical risk. Specifically, the scant amount of disclosure needed by investors to measure their portfolios' physical risk exposure may be one of the reasons behind stock market behavioural biases and inefficiencies in pricing climate change dynamics (Hong et al., 2019; Huynh and Xia, 2021). Some studies found evidence that specific physical risks are embedded into stock price valuations (Bansal et al., 2019; Balvers et al., 2017). However, it is hard to believe that novel measures, such as climate indices (Hong et al., 2019), or satellite data (Ding et al., 2020), may have been the common tool investors have used to assess these risks at the firm level. The former point might be confirmed from the fact that 'alternative data' (to which weather data belongs) may have been historically an informational advantage proper of specific players in financial markets, such as hedge funds (Blank et al., 2019; Katona et al., 2018).

Timing Considerations about Climate Change Risk Pricing

Timing considerations are another critical point to integrate findings at the top-down and bottom-up level. First, it is important to understand how investors perceive climate risks today. Krueger et al. (2020) found that investors have been ranking climate change as the fifth most important risk in their investment process. Notably, policy risk seems to be the most important among the three risks related to climate change proposed in the survey (i.e. together with physical and technological risks). Similar results were found in the surveys by Amel-Zadeh (2021) and CFA (2020).

Additionally, it is relevant to grasp when investors expect climate risks will be financially material for the investment process. On this point, Krueger et al. (2020) showed that investors' responses differ with respect to the particular climate risk analysed. Investors think that policy risk has *already* begun to materialise, a result in line with the CFA (2020) survey. For instance, Atanasova and Schwartz (2019) showed that prices of oil firms are negatively related to their quantities of undeveloped reserves, consistent with the fact that investors have been recognising the possibility these assets may become stranded. However, responses to the surveys given by Krueger et al. (2020) and CFA (2020) showed that investors do not seem concerned about the possibility of a 'carbon bubble'. This result aligns with a study by Griffin et al. (2015), who showed a little equity response to the publication of scientific studies warning about the possibility of non-burnable carbon in the following decades. With respect to other types of climate risks, investor responses match the idea that the true effects of physical, technological and consumer demand risks will be more evident in the long run (Bansal et al., 2019). Specifically, Krueger et al. (2020), in line with Amel-Zadeh (2021) and CFA (2020) surveys, documented that physical risks will threaten the fate of the economy (and related investment decisions) in 5 to 10 years from now. Taken together, these results would indicate that the risk premium identified by Bolton and Kacperczyk (2021a) and Hsu et al. (2023) may reflect a *rational* reward investors require for greater exposure to climate mitigation policies.

Finally, it is important to understand when climate change risks *became* an important topic among the investment management community. In this regard, survey results also converge, indicating that most investors started to consider these risks few years ago. The last point has important implications for linking evidence with the asset pricing tests described in Section 2.3.1. First, this result could explain why studies in Table 2.1, that employ long-term estimation periods when applying asset pricing tests, found evidence of underreaction. The latter is more evident for physical risks (Ding et al., 2020), which, as shown by investor survey results, have received less attention than transition risks.

Second, these types of investor survey responses might also explain why most papers at the bottom-up and top-down levels have revealed that the response to climate change has been stronger over more recent estimation windows, thus supporting the recent market concerns about these risks (Painter, 2020). Specifically, Bansal et al. (2019) found that the temperature elasticity of equity valuations had increased over the years, but such a result does not hold when lower frequencies are considered (as in Griffin et al. (2019)). Alok et al. (2020) and Dessaint and Matray (2017) documented that the salience bias of managers tends to decrease over time, meaning that managers *learn* that extreme weather events effects are not detrimental to how they may think. These outcomes should be read in combination with the recent literature that has shown investors' beliefs to align with both climate mitigation policies proposals and the information disseminated by the scientific community about climate-related topics. This result has been found not only in the (i) real estate market (Baldauf et al., 2020; Bernstein et al., 2019), (ii) municipal bond market (Painter, 2020), (iii) or derivative market (Kruttli et al., 2025; Schlenker and Taylor, 2021), (iv) but in the stock market as well

(Anttila-Hughes, 2016; Griffin et al., 2015; Huynh and Xia, 2021; Sautner et al., 2023b). Notably, such alignment may explain why some arbitrage opportunity has decreased in value in recent years, as Jiang and Weng (2019) found.

Finally, the fact that concerns about climate risks are a recent phenomenon in financial markets has implication for the *sign* of the climate risk premium. Equilibrium models like the one proposed by Pástor et al. (2020) imply that a portfolio of assets hedging climate risks should have a negative premium on an ex-ante basis. However, if investors' began to price these risks only recently, this would imply that the magnitude of unexpected return may dominate over ex-ante considerations about climate risk premiums. These observations should be considered when evaluating the superior performance of sustainable strategies described in Section 2.3.1 over short horizons. In particular, one would conclude that assets providing a hedge to climate risks, such as green stocks, carry a positive (and thus incorrect) climate risk premium (Pástor et al., 2022). Moreover, as the equity market learns how to price climate risks over time, the outperformance of green stocks may be rarely observed in the future.

2.5 Conclusions: Current Gaps and Insights for Future Research in Climate Finance

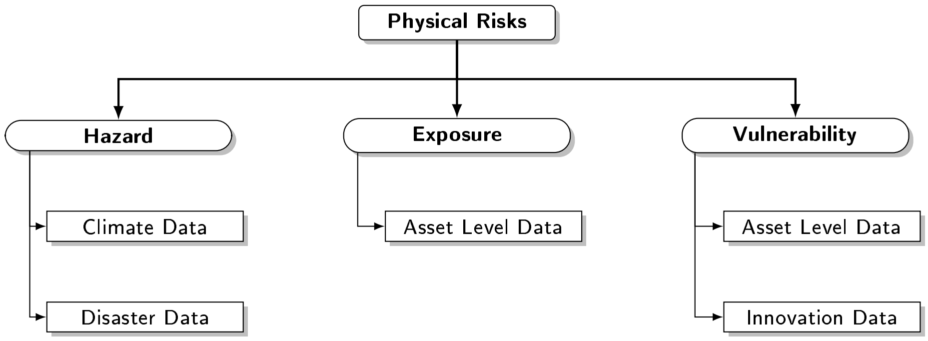
The field of climate finance is new, and the growing interest in the political and industrial debate in recent years has boosted research in this field (Hong et al., 2020). In the near future, collaboration between academics and, in particular, interdisciplinary research could strengthen the knowledge base on how climate risks pose a serious threat to society and, to a greater extent, a systematic risk for financial markets (Barnett, 2023; Battiston et al., 2017; Campiglio et al., 2018; Dietz et al., 2016; Karydas and Xepapadeas, 2019).

Following the quantitative results of climate finance studies at the top-down and bottom-up levels, this chapter reviewed how climate risks may affect the cross section of stock returns, exploring various economic, rational, and behavioural channels.

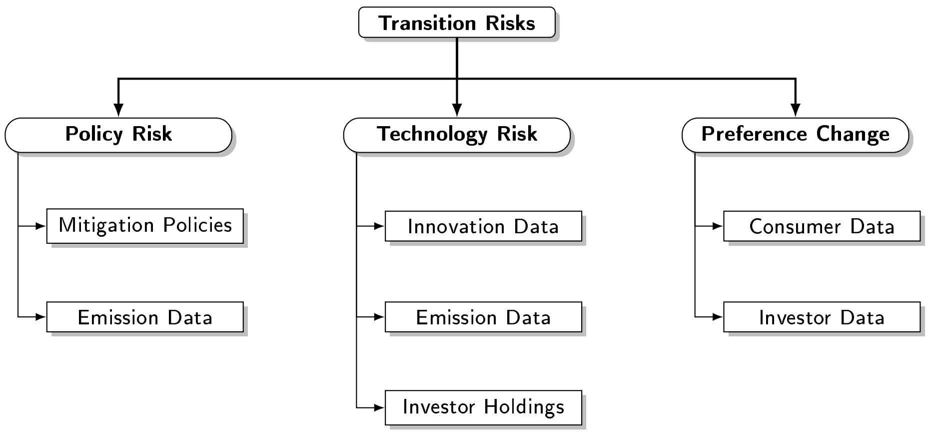
Building on these foundations, this dissertation contributes to the literature on climate finance in several ways. Chapter 3 examines how equity markets price corporate disclosure of physical climate risks in the UK, particularly in the context of material climate-related shocks. Chapter 4 extends this analysis by investigating whether investors differentiate between firms that merely disclose their exposure to physical climate risks and those that also report their corporate adaptation strategies. Finally, Chapter 5 analyses the role of responsible institutional investors in shaping the climate disclosure practices of their investee firms, and examines the capital market consequences of these engagements. Collectively, these chapters aim to advance our understanding of the pricing and demand dynamics of climate-related disclosure in equity markets.

2.6 Figures and Tables

Figure 2.1: Types of data needed to model climate change risks in the equity market.



(a) Types of data needed to model physical risks in the equity market.



(b) Types of data needed to model transition risks in the equity market.

Table 2.1: Climate risk factors and the cross-section of stock returns.

Study	Climate risk measure	Economic rationale	Countries	Sectors	Period	Sample	Is climate risk priced?
Balvers et al. (2017)	Shocks in temperature	Sector and firm dynamics	USA	Multiple	1953-2015	n.a.	
Bansal et al. (2019)	Temperature anomaly	Dividend beta	USA	Multiple	1970-2016	n.a.	
Bolton and Kacperczyk (2021a)	Three emission measures	Transition risk proxies	USA	Multiple	2005-2017	3,421	
Bolton and Kacperczyk (2020)	Three emission measures	Transition risk proxies	77 countries	Multiple	2005-2018	14,400	Yes
Engle et al. (2020)	E-scores	Hedging assets	USA	Multiple	2009-2016	n.a.	
Hsu et al. (2023)	Emission intensity	Climate policy risk	USA	Multiple	1991-2016	503	
Nagar and Schoenfeld (2024)	Text mining index	Economic tracking	USA	Multiple	2003-2019	10,000	
Ardia et al. (2023)	Emission intensity	Pástor et al. (2020)	USA	Multiple	2010-2018	500	
Cheema-Fox et al. (2021)	Two emission measures	Investor irrationality	USA	Multiple	2013-2020	1,002	
Ding et al. (2020)	Soil moisture data	Forecast of firm profit	Multiple	Food	1984-2014	776	
Görgen et al. (2020)	BG scores	Transition risk proxies	Multiple	Multiple	2010-2017	1,657	
Gostlow (2019)	FTS scores	Climate risk proxies	USA, EU and Japan	Multiple	2008-2017	668	
Hong et al. (2019)	PDSI index	Forecast of firm profit	31 Countries	Food	1985-2014	776	No
In et al. (2017) et al	Emission intensity	Investor irrationality	USA	Multiple	2005-2015	739	
Jiang and Weng (2019)	ACI index	Forecast of firm profit	USA and Canada	Food and forestry	1993-2018	145	
Kumar et al. (2019)	Temperature anomaly	Forecast of firm profit	USA	Multiple	1926-2016	n.a.	
Pástor et al. (2022)	E-scores	Pástor et al. (2020)	USA	Multiple	2012-2020	n.a.	

Table 2.2: Climate Risks and Traditional Risk Factors. The table shows the number of traditional systematic factors that have been used from studies in Table 2.1 to adjust for risk exposure when testing eq. (2.4). The columns are related to the excess return on the (i) market factor (MKTRF); (ii) size factor (SMB, Fama and French (1993)); (iii) value factor (HML, Fama and French (1993)); (iv) momentum factor (MOM, Carhart (1997)); (v) liquidity factor (LIQ, Pástor and Stambaugh (2003)); (vi) profitability factor (RMW, Fama and French (2015)); (vii) investment factor (CMA, Fama and French (2015)); and (viii) idiosyncratic risk factor (IDIO, Goyal and Santa-Clara (2003)), respectively.

Study	MKTRF	SMB	HML	MOM	LIQ	RMW	CMA	IDIO	Is climate risk priced?
Balvers et al. (2017)	✓	✓	✓						
Bansal et al. (2019)	✓								
Bolton and Kacperczyk (2021a)	✓	✓	✓	✓	✓		✓	✓	
Bolton and Kacperczyk (2020)	✓	✓	✓	✓				✓	Yes
Engle et al. (2020)	✓	✓	✓						
Hsu et al. (2023)	✓	✓	✓	✓		✓	✓		
Nagar and Schoenfeld (2024)	✓	✓	✓			✓	✓		
Ardia et al. (2023)	✓	✓	✓	✓		✓	✓		
Cheema-Fox et al. (2021)	✓	✓	✓	✓		✓	✓		
Ding et al. (2020)	✓	✓	✓	✓					
Görgen et al. (2020)	✓	✓	✓	✓		✓	✓		
Gostlow (2019)	✓	✓	✓	✓					
Hong et al. (2019)	✓	✓	✓	✓					No
In et al. (2017)	✓	✓	✓	✓		✓	✓		
Jiang and Weng (2019)	✓	✓	✓	✓					
Kumar et al. (2019)	✓	✓	✓	✓					
Pástor et al. (2022)	✓	✓	✓	✓	✓	✓	✓		

Table 2.3: Bottom-up approaches: Firm-level evidence.

Study	Climate risk	Countries	Sectors	Main results	Main asset pricing implications
Addoum et al. (2020)	Extreme temperatures	USA	Multiple	Little operating effects on firms	Temperature risk should not be priced
Addoum et al. (2023)	Extreme temperatures	USA	Multiple	Positive and negative operating effects across sectors	Temperature risk should be priced
Akey and Appel (2021)	Policy risk	USA	Multiple	Corporate parents reallocate their emissions via subsidiaries	Lower market expectations about carbon risk
Bartram et al. (2021)	Policy risk	USA	Multiple	Constrained firms reallocate their emissions in other states	Lower market expectations about carbon risk
Bolton and Kacperczyk (2021b)	Technology risk	66 countries	Multiple	Green firms reduce emissions more than brown firms	Possible unexpected and positive revaluations for green stocks
Dai et al. (2021)	Preference change	USA	Multiple	Costumers hinder the reallocations of emission of their suppliers	Higher market expectations about carbon risk
De Haas et al. (2021)	Technology risk	22 countries	Multiple	Constrained firms do not adopt low-carbon investment strategies	Constrained firms may be more exposed to long-term technology risks
Huynh and Xia (2021)	Natural disasters	USA	Multiple	Negative operating impacts across firm establishments	Natural disaster risks should be priced
Lv and Bai (2021)	Technology risk	China	Energy	Increase in the amount of R&D after the introduction of a mitigation policy	Possible unexpected ad positive revaluations for brown stocks
Pankratz et al. (2023a)	Extreme temperatures	57 countries	Multiple	Negative operating effects for SMEs	Temperature risk should be priced
Pankratz and Schiller (2024)	Extreme temperature and floods	71 countries	Multiple	Negative operating effects on supplier and corporate costumers	Physical risks may be a systematic risk
Rao et al. (2021)	Extreme precipitation	India	Multiple	Long-lasting operating effects on impacted firms	Precipitation risk should be priced
Trinks et al. (2020)	Technology risk	47 countries	Multiple	Carbon-efficient firms have higher operating performances	Possible unexpected and positive revaluations for green stocks
Xu and Kim (2021)	Policy risk	USA	Multiple	Constrained firms reallocate their emissions in other states	Lower market expectations about carbon risk

Table 2.4: Bottom-up approaches: Investor-level evidence.

Study	Financial actors	Countries	Period	Main Results	Main asset pricing implications
Akey and Appel (2019)	Hedge funds	USA	1991–2015	Hedge funds are engaging with firms to foster carbon management practices	Investors are pricing carbon risk at the firm level
Alok et al. (2020)	Fund managers	USA	1995–2016	Fund managers overreact to natural disasters	Price reversal for exposed stocks
Amel-Zadeh (2021)	Institutional	-	-	Climate risks are a recent phenomenon in the financial industry	Estimating the correct sign of the climate risk premium may be challenging
Atanasova and Schwartz (2019)	Whole market	USA	1999–2018	Oil stock prices are negatively related to their quantities of unproved reserves	Investors are pricing carbon risk at the firm level
Azar et al. (2021)	Mutual funds	USA	2005-2018	Mutual funds are engaging with firms to foster carbon management practices	Investors are pricing carbon risk at the firm level
CFA (2020)	Institutional	-	-	Lack of disclosure does not foster a correct pricing of climate risks	Possible underpricing of climate risks because of a lack of disclosure from firms
Choi et al. (2020)	Retail investors	64 countries	2001–2017	Investors demand green stocks during extremely hot months	Negative climate beta for green stocks
Flammer et al. (2021)	Institutional	USA	2010–2016	Investors are engaging with firms to increase the amount of climate-related disclosure	Investors value climate risk disclosure positively
Griffin et al. (2019)	Whole market	USA	2003–2017	Excess returns are lower when accounting for the size and value premiums	Temperature risks may be related to a size or a value effect
Huynh and Xia (2021)	Whole market	USA	1990–2015	Investors overreact to natural disasters	Price reversal for exposed stocks
Ilhan et al. (2023b)	Institutional	-	-	Lack of disclosure does not foster a correct pricing of climate risks	Possible underpricing of climate risks because of a lack of disclosure from firms
Krueger et al. (2020)	Institutional	-	-	Climate risks are a recent phenomenon	Estimating the correct sign of the climate risk premium may be challenging
Pankratz et al. (2023a)	Analysts	57 countries	1995–2017	Earnings surprises due to unanticipated extreme temperatures exposure	Anticipating physical risks may be challenging for investors
Ramelli et al. (2021)	Whole market	USA	2016–2020	Investors demand green stocks during events of policy uncertainty	Negative climate beta for green stocks

Chapter 3

Physical Climate Risk Disclosure: Does Corporate Transparency Pay Off?

3.1 Introduction

As discussed in Chapter 2, a growing literature in climate finance examines the impact of climate risk disclosure on firm value. Recent studies have begun to explore how equity investors incorporate information about firms' exposure to physical climate risks (such as those stemming from a warming planet or extreme weather events) into asset prices, with a predominant focus on US firms (see, e.g., Nagar and Schoenfeld 2024; Matsumura et al. 2024). However, no empirical study to date has systematically assessed how UK investors price such disclosures. This chapter addresses this gap by investigating the stock market implications of physical climate risk disclosures by UK-listed firms. Historically, UK companies have exercised significant discretion in reporting their exposure to physical climate risks to capital markets (EY, 2017), offering a unique setting to examine the informational value of such disclosures and their effect on investor uncertainty when the risks are financially material.

Physical climate risk disclosures, by potentially reducing information asymmetries, are expected to enhance the liquidity of a firm's securities following climate-related shocks (Diamond and Verrecchia, 1991), thereby preserving firm value (Easley and O'hara, 2004). Two mechanisms are particularly salient in this context. First, disclosure informs investors about the magnitude of potential exposures and the firm's mitigation strategies, thereby enabling a more accurate valuation of expected post-disaster performance. Second, and not mutually exclusive, is the notion that disclosure helps investors manage ambiguity when physical climate risks materialise. If so, firms that disclose such risks should experience smaller reductions in stock liquidity during climate-related events. This chapter examines how physical climate risk disclosures influence firm value, drawing on theories of corporate disclosure and asset pricing. The former predicts how disclosure affects investor uncertainty and thus firm value, while the latter provides a robust empirical framework for testing these effects.

We make two principal contributions. First, we provide the first firm-level evidence on how investors price physical climate risk disclosure among UK-listed companies. Using textual analysis of annual reports and a tailored climate-related lexicon, we distinguish between disclosing and non-disclosing firms. This approach enables us to identify firms providing material disclosures about their exposure to physical climate risks, as opposed to those with minimal or no disclosure (Nagar and Schoenfeld, 2024). We then assess how investors price these disclosures by treating natural disasters as exogenous shocks to investors' uncertainty about firms' fundamentals (often referred to as information uncertainty (Epstein and Schneider, 2008)). We find that disclosing firms experience significantly smaller cumulative abnormal returns (CARs) around natural disaster events relative to non-disclosing peers. Specifically, disclosing firms exhibit an average CAR decline of approximately 1.2%, compared to 2.3% for similarly affected but non-disclosing firms. Placebo tests confirm the robustness of these findings.

These findings contribute to the broader debate in climate finance regarding the value relevance of climate-related disclosure. Contrary to some US-based studies (e.g., Nagar and Schoenfeld 2024; Berkman et al. 2024), which find that disclosure may invite investor penalisation due to litigation risk or perceived weakness, our results suggest that UK firms are rewarded for greater transparency. This divergence may be attributable to the relatively lower litigation risk in the UK, a less litigious jurisdiction.[1] Our evidence thereby opens new avenues for cross-country research into the pricing of climate risk and the institutional factors that mediate this relationship.

Second, our analysis sheds light on the mechanisms underlying these valuation effects. We show that the attenuation of market penalties is driven by a reduction in investor uncertainty. By examining changes in stock liquidity, a proxy for information uncertainty (Rehse et al., 2019), we show that liquidity remains higher for disclosing firms during disaster events. This finding is consistent with the theoretical predictions of Guay and Verrecchia (2018), which suggest that disclosure of adverse information mitigates investor uncertainty and stabilises firm valuations under conditions of heightened information asymmetry. Importantly, we find no significant differences in operating cash flows or return volatility between disclosing and non-disclosing firms following disasters, allowing us to rule out both cash flow- and risk-based explanations (Nagar and Schoenfeld, 2024; Liu et al., 2017). Our results are thus most consistent with the hypothesis that disclosure reduces investor ambiguity, leading to more resilient market valuations.

[1] See Berezow, A. (2019). “Blame and Claim: Can We Fix America’s Uniquely Litigious Culture?” https://www.acsh.org/news/2019/12/27/blame-and-claim-can-we-fix-americas-uniquely-litigious-culture-14477

Our results have clear policy implications. As climate-related risks intensify and investor demand for transparency grows, our findings support regulatory efforts to enhance firm-level disclosure of physical climate risks. Such disclosures not only improve market functioning by reducing ambiguity but may also bolster financial stability by protecting firms from valuation losses in the aftermath of natural disasters. Policymakers and standard-setters should thus view climate risk disclosure not merely as a sustainability reporting tool, but as a key mechanism for promoting investor protection and market resilience.

The remainder of the chapter is structured as follows. Section 3.2 provides background on the UK regulatory context and prior literature related to climate risk disclosure. Section 3.3 develops the theoretical framework and hypotheses. Section 3.4 describes our data and presents descriptive statistics. Section 3.5 outlines the methodology for constructing the physical climate risk disclosure measure. Section 3.6 presents our empirical strategy and model specifications. Section 3.7 reports the results and investigates the potential underlying channels. Section 3.8 concludes.

3.2 Background: Physical Climate Risk Disclosure in UK Annual Reports

Over recent decades, the United Kingdom has been among the most pioneering jurisdictions in the regulation of firm-level climate change disclosure (Jouvenot and Krueger, 2022). This effort forms part of the broader strategy of the UK Government to consolidate its leadership in international climate policy (Lorenzoni et al., 2007). The UK has implemented a series of domestic legal instruments linking national policy objectives to the outcomes of international climate negotiations (e.g., the Kyoto Protocol) and to the scientific findings of the Intergovernmental Panel on Climate Change (IPCC). In this context, mandatory climate-related disclosure has become a central regulatory mechanism for aligning corporate behaviour with national commitments to decarbonisation and climate resilience.

The UK's early initiatives focused primarily on carbon reporting and mitigation. The 2008 *Climate Change Act* made the UK the first country to introduce legally binding carbon budgets, targeting an 80% reduction in greenhouse gas emissions by 2050 relative to 1990 levels (Lockwood, 2013). Subsequently, the *Companies Act 2006 (Strategic and Directors' Reports) Regulations 2013* required UK-incorporated firms listed on the Main Market of the London Stock Exchange to disclose their greenhouse gas emissions in annual reports. Empirical studies document that this regulation had both real and financial effects: firms subject to the requirement reduced their emissions relative to comparable European peers, while investors penalised those disclosing high emissions due to expectations of higher future compliance costs (Downar et al., 2021; Jouvenot and Krueger, 2022; Bolton and Kacperczyk, 2020).

Building on this foundation, the UK established one of the most comprehensive mandatory disclosure frameworks globally by aligning its regime with the recommendations of the *Task Force on Climate-related Financial Disclosures* (TCFD). Since April 2022, large UK-incorporated companies, LLPs, and listed issuers have been legally required to disclose information on climate-related governance, strategy, risk management, and metrics and targets in their annual reports. The Financial Conduct Authority (FCA) enforces these requirements for listed entities, providing regulatory clarity and enhancing comparability across firms. This centralised, rules-based approach supports investors' ability to assess and price climate-related risks. The UK is now in the process of transitioning from the TCFD framework to the ISSB-aligned *UK Sustainability Disclosure Standards*, which are expected to further harmonise domestic reporting with emerging international norms.

By contrast, the United States has pursued a more fragmented and contested regulatory path. Although the Securities and Exchange Commission adopted a climate disclosure rule in March 2024, its implementation is currently stayed pending litigation. In the absence of a uniform federal standard, U.S. disclosure practices are being shaped primarily by state-level legislation, most notably California's, which mandate greenhouse gas emissions disclosure and climate risk reporting for large companies starting in 2026–2027.[2] This regulatory fragmentation may potentially generate uncertainty and potential compliance burdens for firms operating across multiple jurisdictions. However, it also reflects broader political-economic dynamics surrounding climate policy in the U.S., including legal challenges based on administrative and constitutional grounds.

Overall, the UK's centralised and mandatory disclosure framework contrasts with the U.S. model, which remains decentralised and litigation-driven. The UK regime offers regulatory stability and international alignment, whereas the U.S. approach continues to evolve through state-level experimentation, investor pressure, and ongoing judicial contestation. Against this backdrop, the present study focuses on an underexplored dimension of UK climate disclosure: the reporting of physical climate risks. Despite the UK's leadership in carbon and transition-risk disclosure, guidance specific to physical risks has been comparatively limited (there is, for example, no UK equivalent to the SEC's 2010 *Climate Change Guidance*). Instead, firms have largely relied on general international accounting standards for reporting the financial effects of natural disasters (EY, 2017). This study therefore seeks to provide empirical evidence on UK firms' physical climate risk disclosure practices and on how investors incorporate such information into asset prices.

[2] For more information, see `https://www.keyesg.com/article/preparing-your-business-for-the-california-climate-disclosure-laws`.

3.3 Hypothesis Development

Asset pricing models of information uncertainty predict that, in equilibrium, information uncertainty commands an ambiguity premium (Epstein and Schneider, 2008). In our context, information uncertainty refers to investors' uncertainty arising from both past and new information relevant for estimating firm value. In this paper, we focus on the information uncertainty triggered by natural disaster events, which allows us to consider both sources. Specifically, natural disasters represent exogenous shocks that increase not only uncertainty about the *future* quality of information regarding firm fundamentals, but also require investors to reinterpret the meaning and implications of *past* corporate disclosures concerning physical climate risks.

Natural disasters constitute an exogenous increase in information uncertainty, as they introduce conditions under which the probability distribution of potential outcomes cannot be reliably estimated. As shown by Rehse et al. (2019), natural disaster events such as Hurricane Sandy generate Knightian uncertainty rather than measurable risk, since investors cannot form credible expectations about the magnitude, location, or persistence of damages. In particular, this ambiguity concerns whether the disruption will be temporary or structural, how quickly firms' operations and supply chains might recover, and whether assets have been permanently impaired. The difficulty of quantifying these consequences compels investors to reassess firms' valuations under incomplete information, leading to wider bid–ask spreads, reduced trading volumes, and overall market illiquidity. These empirical patterns are consistent with theories of ambiguity aversion (Epstein and Schneider, 2008). In this context, natural disasters serve as quasi-experimental shocks to uncertainty: they instantaneously disrupt the information environment without being driven by economic fundamentals, making them an established setting in the literature for studying how markets price information ambiguity (Rehse et al., 2019).

However, disclosure of physical climate risks prior to a disaster can mitigate the negative effects of information uncertainty on firm value during natural disasters for several reasons. First, such disclosures provide investors with ex-ante information about a firm's exposure to climate-related risks, enabling a better assessment of potential impacts on operations, supply chains, or infrastructure. Second, firms that disclose physical climate risks may signal a commitment to several risk management practices, thereby improving investor confidence in the firm's ability to mitigate disaster-related losses (Pankratz et al., 2023b). Third, these disclosures facilitate a more informed reinterpretation of past financial statements and operational data when a disaster occurs, reducing the likelihood of market overreactions or mispricing. Overall, these disclosures mitigate the ambiguity premium by narrowing the range of plausible outcomes that investors must consider in the aftermath of a natural disaster.

Based on this reasoning, we propose the following hypotheses:

Hypothesis 1A: *Natural disaster events create information uncertainty at the firm level, leading to negative returns for disaster-affected firms.*

Hypothesis 1B: *Disclosure of physical climate risks mitigates the negative effects of information uncertainty on stock returns when a company is impacted by a natural disaster.*

The theory of asset pricing provides a rigorous framework for analysing the channels underlying firm value effects around natural disaster events: a decline in future cash flows (Nagar and Schoenfeld, 2024), which we refer to as the "cash flow channel," and an increase in the premium required by investors due to information uncertainty (Epstein and Schneider, 2008), which we denote the "discount rate channel." Regarding the first channel, natural disasters may cause physical damage and operational disruptions that translate into lower revenues or higher costs, thus reducing earnings for affected firms. These fundamental shocks can persist well beyond the immediate aftermath of the event, reflecting repairs, supply chain reconfiguration, or strategic repositioning (Huynh and Xia, 2021). However, firms that disclose their physical climate risks in advance may provide investors with information about the magnitude of potential exposures, as well as the robustness of contingency planning and risk mitigation strategies. Such transparency may help investors better anticipate and price the impact of natural disasters on the firm's long-term financial performance. We state the cash flow channel hypothesis as follows:

Hypothesis 2A (Cash flow hypothesis): *Expected cash flows decrease after a natural disaster, but less so for impacted firms that disclose physical climate risks.*

In addition to long-term effects on fundamentals, natural disasters can create significant short-term information uncertainty. Investors may face challenges in assessing the extent of physical damage, the timeline for recovery, and the broader financial implications. We examine this discount rate channel by analysing changes in stock liquidity around natural disaster events. Asset pricing theory suggests that *ambiguity*-averse investors reduce trading activity when they anticipate increased information uncertainty (Rehse et al., 2019). Consequently, a decline in stock liquidity following a natural disaster would be consistent with investors demanding a higher ambiguity premium (Epstein and Schneider, 2008). However, if physical climate risk disclosures help investors mitigate such ambiguity, we expect the drop in liquidity to be smaller for firms that disclose these risks. This leads to the following hypothesis:

Hypothesis 2B (Climate uncertainty hypothesis): *Stock illiquidity increases after natural disasters, but less so for impacted firms that disclose physical climate risks.*

3.4 Data and Descriptive Statistics

We now explain the four main sources of data used to build the measures required to test our hypotheses. We also provide summary statistics for these measures throughout the following subsections.

3.4.1 UK Annual Reports

To gauge companies' disclosure of physical climate risks, we retrieved corporate annual reports (in PDF format) for all UK firms listed on the London Stock Exchange (LSE) for fiscal year-ends between January 1996 and December 2018. We relied on Thomson Reuters Eikon as our main source of textual data, supplementing it with information from Companies House when a generic annual report was unavailable in a given year. In Appendix 3.10.1, we provide details about the procedure we followed to extract text in a machine-readable format from PDF documents.

Using annual reports for measuring physical climate risk disclosure at the firm level has two main advantages. First, all companies listed on the LSE are legally required to file a corporate report on an annual basis. This is important, as our sample may mitigate possible selection bias concerns that can arise when focusing on voluntary disclosure sources (such as earnings conference calls or disclosure to the Carbon Disclosure Project (CDP)). Second, unlike CDP surveys, the disclosure templates of UK annual reports are unstandardised, and the firm's management has considerable discretion in structuring corporate information (El-Haj et al., 2020). This kind of flexibility in corporate reporting is particularly relevant for identifying cross-sectional heterogeneity in physical climate risk disclosure across and within industries, as opposed to standardised templates that might limit the depth and variety of information provided to investors.

3.4.2 Firm Characteristics and Stock-level Data

We matched annual report data with accounting data in British Pounds (GBP) from Worldscope, Financial Analysis Made Easy (FAME), and Compustat Global. Importantly, we also obtained information on firms' fiscal-year-end reporting schedules to accurately merge yearly financial records with annual report information. We then applied the following filters. First, following Jouvenot and Krueger (2022), we removed firm-year observations with annual sales growth exceeding 500% and negative assets or revenues. Second, we excluded from our analysis all firms categorised as "Financials" according to the Industry Classification Benchmark (ICB) classification system.[3] This last exclusion allowed us to focus solely on firms that may utilise hedging instruments against physical climate risk. Financial companies, on the other hand, may mention climate hedging instruments in their annual reports as suppliers of such instruments rather than end-users.

We retrieved data on stock returns and liquidity from Thomson Reuters DataStream. As noted from a large literature in finance, Thomson Reuters DataStream may suffer from data errors ((Choi et al., 2020; Ince and Porter, 2006; Landis and Skouras, 2021), among others). To address this concern, we followed the data-filtering guidelines proposed by Landis and Skouras (2021), which build upon prior recommendations described in the asset pricing literature, such as those provided by Ince and Porter (2006).[4] Finally, we gathered data on analysts' earnings forecasts from the Institutional Brokers' Estimate System (IBES) to distinguish between the cash flow and discount rate hypotheses in our asset-pricing tests. Table 3.1, Panel B, presents summary statistics for the main financial variables used in the analysis, and Table A.3.1 provides the definitions of these variables.

[3]The ICB is the classification system used for companies listed on the London Stock Exchange. For more information, see: `https://www.ftserussell.com/data/industry-classification-benchmark-icb`

[4]See Table 1 in Landis and Skouras (2021) for the list of filters applied in our analysis to clean stock returns data.

3.4.3 Firm Locations and Corporate Ownership Structure

We use FAME as our primary data source for data on the geographic locations at the city or town level of firms' headquarters and their global subsidiaries and on corporate linkages between parent companies and their subsidiaries.[5] Given that the ownership structure information in FAME is "static" at the time of the download, we used textual information available in companies' annual reports to generate a *dynamic* ownership structure over the study period. This approach is suitable given that UK-listed firms are required to disclose their ownership structure to comply with "Regulation SI 2015/980".[6] In line with the literature on corporate governance, we considered a shareholder firm as a parent if it holds more than 20% of the voting rights in a specific subsidiary during a given year (Aminadav and Papaioannou, 2020). This filter left 45,738 unique UK subsidiaries. Then, for each firm and each year, we checked whether a particular subsidiary name, as provided in FAME, was referenced in the annual report of its parent-listed company. We followed O'Donovan et al. (2019) to operationalise this and set a maximum threshold of 80% Levenshtein distance between the subsidiary name and how it appears in the parent's annual report.[7] After applying these filters, we identified 41,929 subsidiaries during the study period. Panel A of Figure 3.1 shows that the distribution of subsidiaries is concentrated in G7 countries (namely, Canada, Germany, France, Italy, Japan, the UK, and the United States), accounting for 73.72% of the subsidiaries' locations. Panel A of Figure 3.2 shows the geographic distribution of parent headquarters and their subsidiaries in the UK. Although most firms are located in the

[5]Furthermore, if the parent or subsidiary address was missing, we manually checked the data and collected information from Dun & Bradstreet and country-specific news websites.

[6]The Regulations which implement the EU Accounting Directive (SI 2015/980) removed the possibility under the "s410 Companies Act 2006" through which UK companies were allowed to list only their *principal* subsidiaries in their annual reports. Therefore, although the completeness of subsidiaries reporting may have been lower before the "Regulation SI 2015/980", our strategy allows us to focus only on the most relevant holdings before the law came into effect.

[7]The main results of the paper are unchanged when we use a threshold of 100%.

Greater London Area, parent companies and their subsidiaries have considerable geographic dispersion across the country.

We provide additional information in Table A.3.2 to further shed light on the characteristics of the geographical distribution of firm locations in our sample. In Panel A, Table A.3.2, we report summary statistics about the number of firm locations, distinguishing between parent firms with a single location (i.e., only the headquarters), those with subsidiaries located only in the UK, and those with at least one foreign subsidiary. Panel A, Table A.3.2, reveals two main patterns. First, unexpectedly, firms with at least one foreign subsidiary have on average the highest number of subsidiaries across companies. Second, the majority of firms (62% of the sample) have corporate facilities located only in the UK. Specifically, 27% of the firms have, on average, eight subsidiaries located in the UK, while 35% of companies in the sample have only their headquarters as a corporate location.

Panel B, Table A.3.2, reports the distance, measured in kilometres, of corporate subsidiaries from the location of the parents' headquarter. Panel B shows that, on average, parent companies with at least one foreign subsidiary are situated 3,521 kilometres away from their subsidiaries. However, it is also important to note the high standard deviation of this distance, considering that these parent firms may also have subsidiaries located in the UK. Finally, Panel B shows that parents having only subsidiaries in the UK are located on average 37 kilometres away from these subsidiaries. Notably, 75% of these parent firms are located zero kilometres away from their domestic subsidiaries, meaning that these corporate locations are situated in the same city or town of the parent headquarters.

Overall, anecdotal evidence from Table A.3.2 suggests that despite the global scale of corporate locations, we are likely capturing significant *group*-level activities around parents' headquarters for most firms in our sample. This implies that, in most cases, a natural disaster affecting the headquarter will also impact on the majority of the firm's operations. In the next subsection, we explain how we account for the heterogeneity in foreign and domestic corporate locations when constructing variables to measure material physical climate risk exposure at the firm level.

3.4.4 Natural Disasters

We gathered data on natural disasters from the Geocoded Disasters (GDIS) dataset (Rosvold and Buhaug, 2021). GDIS represents the geocoded version of the Emergency Events Database (EM-DAT). The latter is one of the most important datasets providing information about natural disasters worldwide, and it is widely used in the climate finance literature (e.g., Pankratz and Schiller (2024)). By merging the EM-DAT dataset with GDIS, we can retrieve information about: (i) economic (dollar) damage caused by each event; (ii) the type of natural disaster event; (iii) the spatial geometry in the form of GIS polygons for different administrative entities listed as "disaster locations" in the EM-DAT dataset; and (iv) the day, month, and year of the natural disaster event. We applied the following filters to the merged GDIS/EM-DAT dataset. First, we converted the economic dollar amounts in EMDAT into British pounds and required that a natural disaster event caused at least £100 million in 2018 constant pounds. Second, we retained only natural disasters related to one of the following categories: (i) meteorological, (ii) hydrological, or (iii) climatological. We narrowed our focus to these kinds of natural disasters due to their direct relevance to climate change dynamics (Huang et al., 2022). As a result, we filtered out geophysical disasters, given the limited evidence that geophysical disasters are changing in response to climate change.[8]

Our main measure of material exposure to physical climate risks is a dummy variable, $D_{i,t}^{\text{Impacted}}$, which equals one if at least either a firm's headquarters or one of its subsidiaries is situated in an area that has been

[8] For a discussion about this point, see for example: `https://climate.nasa.gov/news/2926/can-climate-affect-earthquakes-or-are-the-connections-shaky/`

affected by a natural disaster, and zero otherwise. It is important to stress that GDIS provides information on only one of the three types of administrative levels affected by a natural hazard within a country. In other words, it could provide administrative level 1 (ADL1) information (which, in the UK, would be country level), ADL2 information (county level[9]) or ADL3 information (district, civil parish, commune or village level[10]) in the form of GIS polygons. Given the relatively limited frequency with which ADL3 information is provided in GDIS, we restricted our analysis to ADL1 and ADL2 for our empirical tests. However, to ensure completeness, we converted any natural disaster reported with ADL3 granularity into the relevant ADL2 and ADL1 polygons. For example, we listed the flood event coded as "2014-0039-GBR" in EM-DAT, which affected the civil parish of Yeovil (ADL3) in the UK, as affecting the county of Somerset (ADL2) and England (ADL1), by retrieving the respective GIS polygons from GADM for both administrative units. We applied the same procedure to obtain GIS polygons for the first administrative units from GADM if only the second administrative unit polygons were provided in GDIS. Therefore, throughout the paper, we created different specifications of the $D_{i,t}^{\text{Impacted}}$ variable, with a focus on the ADL1 and ADL2 granularities of the areas affected by a natural disaster, as well as the type of firm location affected by the natural hazard (i.e., either the parent's headquarters, one of its subsidiaries, or both).

Figure 3.1, Panel A, displays a heatmap of UK firms' locations exposed to natural disasters at the first administrative level worldwide. Notably, Figure 3.1, Panel A, indicates the importance of identifying natural disaster expos-

[9]Importantly, we rely on the county classification provided in GADM to analyse natural disasters at the second-administrative level in the UK. GADM is the dataset used in Rosvold and Buhaug (2021) to construct GIS polygons.

[10]ADL3 usually represents districts, communes, or villages, depending on the country. For example, in England, the administrative level 3 is equivalent to the district level, which is subdivided into wards. In Scotland, the administrative level 3 is equivalent to the council area level, which is subdivided into electoral wards. In Wales, the administrative level 3 is equivalent to the principal area level, which is subdivided into communities. In Northern Ireland, the administrative level 3 is equivalent to the district level, which is subdivided into wards.

ure at a more granular level when analysing international samples. This is particularly relevant due to the within-country heterogeneity in natural disaster hazards. Figure 3.2, Panel B, illustrates a heatmap of firms' locations exposed to natural disasters at the second administrative level in the UK. Again, the county level heterogeneity indicates that higher granularity (i.e., ADL2 as opposed to ADL1 in the UK) in natural disaster exposure is relevant for our empirical tests, as it provides a more precise identification strategy when defining natural disaster-impacted and unimpacted firms.

3.5 Physical Climate Risk Measures

3.5.1 Measurement

We measure firm-level physical climate risk disclosure through the textual analysis of UK annual reports and one purpose-built dictionary. Specifically, we constructed a lexicon with relevant physical climate risk terms through a two-step process. First, we collected natural disaster-related keywords from established sources: namely the SENDAI framework for Disaster Risk Reduction and the IRDR Peril Classification and Hazard Glossary.[11] As in Li et al. (2024), we augmented these lists using additional sources, such as meteorology books and Wikipedia lists. Our first textual measure proxying for physical climate risk at the firm level is the physical climate risk ratio, or $\text{TM}_{i,t}^{\text{High Exposure}}$. To construct this variable, we count all the natural disaster unigrams that are associated with unambiguous bigrams (i.e., combination of two words). Bigrams are first identified by searching for all the possible combinations of natural disaster unigrams with previous or subsequent words appearing in corporate annual reports. Next, we manually

[11]The latter is the same used from EM-DAT to provide disaster classifications. For more information, see: `https://www.emdat.be/guidelines#_ftn1`

delete the bigrams that appear to be false positives.[12] We instead included unigrams in our final lexicon if the associated bigrams were unambiguous in their use within the context of climate-related topics. The final dictionary consists of 50 unigrams and 2,596 bigrams. Therefore, $\mathrm{TM}_{i,t}^{\text{High Exposure}}$ will be the number of occurrences of unigrams and bigrams related to natural hazards divided by the total number of words in the annual report. We rescale the $\mathrm{TM}_{i,t}^{\text{High Exposure}}$ variable, so that it varies between 0 and 1, to ease the interpretation of our validation tests.

3.5.2 Descriptive Findings

In this section, we present preliminary evidence on the characteristics of our physical climate risk measure. Table A.3.3 reports the most common physical climate risk keywords identified in climate-related corporate disclosures. Two results emerge from Table A.3.3. First, the term "*weather*" appears as the most frequently cited keyword when UK firms discuss physical climate risks. Prior research has shown that this term can be associated with both acute (Nagar and Schoenfeld, 2024) and chronic (Li et al., 2024) climate risk exposures at the firm level, suggesting that references to weather may serve as a broad indicator of physical climate risk concerns. Second, flood-related risks (evident in keywords such as "flooding," "floods," and "flood damage") represent the predominant category of natural hazards mentioned by UK firms. This finding aligns with anecdotal evidence found in the interviews of Tang (2022), which highlights that physical risks from flooding are a primary concern for UK managers.

Subsequently, we examine industry-specific patterns. Table A.3.4 reports the mean values ranked by industry for the physical climate risk measure. Consistent with previous findings in the literature (Li et al., 2024; Sautner

[12] For example, we excluded bigrams where the term 'flood' was preceded by 'Sharon', referring to the Chairman of the Audit and Risk Committee at Pets at Home Group PLC, Sharon Flood.

et al., 2023a), companies operating in sectors related to Utility, Food, Beverage, and Tobacco, as well as Basic Resources and Energy exhibit high levels of physical climate risk exposure. As noted in Li et al. (2024), firms operating in these sectors have significant exposure to disruptions caused by physical climate risks, given that a substantial portion of their corporate activities occurs outdoors. However, even if the variation in physical climate risk disclosure that we detect across industries may be explained by industry-inherent factors (Goldstein et al., 2019), it is important to note in Table A.3.4 that the heterogeneity persists also *within* each industry. This observation becomes evident when examining the high standard deviation in the physical climate risk measure for each industry. Such considerable within-industry variation underscores the importance of controlling for firm-specific, time-invariant characteristics in our empirical analysis. Therefore, we include firm fixed effects in our regression models to ensure that our results are not driven by unobserved heterogeneity at the firm level, and to isolate the impact of changes in physical climate risk exposure over time within individual firms.

Finally, Table A.3.5 reports excerpts from the annual reports of firms with the highest values of $\text{TM}_{i,t}^{\text{High Exposure}}$. Consistent with the information in Table A.3.4, Table A.3.5 provides anecdotal evidence that several companies across different sectors are exposed to threats from physical climate risks, spanning, for example, from flood to wildfire risks. Interestingly, while some firms report solely on their physical climate risk exposure, others also inform investors about the adaptation strategies they are implementing to manage these risks.[13] The aim of this chapter is to understand how such disclosures influence investor uncertainty when the risks being addressed are material.

[13]I analyse how investors price climate adaptation disclosure in chapter 4.

3.5.3 Validation

To validate the physical climate risk measure, we need to ensure that it accurately captures material climate risk exposure at the firm level. To test this, we employed a multivariate regression framework and estimated the following model:

$$\mathrm{TM}_{i,t}^{\text{High Exposure}} = \alpha + \beta_1 \; D_{i,t}^{\text{Impacted}} + \gamma \; \mathbf{X}_{i,t} + \theta_i + \vartheta_t + e_{i,t} \tag{3.1}$$

where $\mathrm{TM}_{i,t}^{\text{High Exposure}}$ is the physical climate risk measure based on the annual report of firm i for fiscal year t. $D_{i,t}^{\text{Impacted}}$ is a binary variable that equals one if a firm's location (headquarter or subsidiary) is affected by a natural disaster during the fiscal-year period t. $\mathbf{X_{i,t}}$ is the same set of control variables employed by Li et al. (2024), including log of total assets, property, plants and equipment, return on assets (ROA), capital expenditures and leverage. Since physical climate risk varies across firms and time, we incorporate both firm fixed effects (θ_i) and year fixed effects (ϑ_t). We clustered standard errors conservatively at the firm and year levels (Petersen, 2008).

We report the results of eq. (3.1) in Table 3.2. The results in Column (1) reveal that the text measure of firms located in areas affected at the first administrative level worldwide is 0.7% higher than that of unaffected firms, significant at the 5% level. However, such an identification strategy may be too coarse, as certain administrative regions globally might be too large to ensure that a natural disaster occurring in these regions can have a definite impact on a company's operations. Indeed, we demonstrate that this difference becomes more statistically significant and slightly higher in magnitude when we focus on more granular administrative divisions (level 2). Specifically, Column (4) shows that the text measure of firms located in areas affected at the second administrative level worldwide is 0.8% higher than that of unaffected firms, significant at the 1% level.

We then considered alternative specifications of the $D_{i,t}^{\text{Impacted}}$ variable in eq. (3.1) to identify which specific type of firm location affected by natural hazards is driving variation in the physical climate risk measure. Column (2) shows that the positive association between the text measure and natural disasters at the first administrative level is driven by exposure at the headquarters level, rather than at the subsidiary level. We observe similar results when focusing on natural hazards that impacted firm locations at the second administrative level, as reported in Column (5). We also analysed whether these results changed when further considering natural disaster impacts affecting either a domestic or foreign subsidiary. However, the regression estimates in Columns (3) and (6) show that the effect remains statistically significant only for natural disaster exposure at the headquarter level, regardless of whether such exposure occurs at the first or second administrative levels.

Overall, the evidence shown in Table 3.2 is important for at least two reasons. First, it substantiates the notion that the physical climate risk ratio measure can readily capture firms' exposure to natural disaster events, an important determinant of physical climate risk. Second, the results are also consistent with the evidence shown in Table A.3.2 (discussed in Section 3.4.3), which indicates that most firms in our sample have *group*-level activities located around their headquarters. The finding that variation in the physical climate risk measure is driven by exposure at the headquarters level reinforces the idea that, cross-sectionally, managers may consider natural disaster impacts on this type of corporate location as particularly significant for companies' operations.

3.6 Model Specification

To investigate the firm value implications of company transparency about physical climate risk exposure, we employed an event study methodology. Event studies are prevalent in the climate finance literature ((Jouvenot and Krueger, 2022; Nagar and Schoenfeld, 2024), among others) and are well-suited for testing the hypotheses formulated in Section 3.3. Following established practice in the climate finance literature, the only additional filter we set with respect to those introduced for natural disasters in Section 3.4.4 is that the duration of a natural disaster did not exceed 30 days (Huynh and Xia, 2021).

The event-study panel specifications used for our analysis follow the logic of staggered treatment designs and are similar in spirit to the framework suggested by Baker et al. (2022):

$$\begin{aligned}\mathrm{CAR}_{i,t}[-5,+5] = \;& \alpha + \beta_1 D_{i,t}^{\text{Impacted}} + \beta_2 D_{i,t-1}^{\text{High Exposure}} \\ & + \beta_3 D_{i,t}^{\text{Impacted}} \cdot D_{i,t-1}^{\text{High Exposure}} + \gamma \mathbf{X}_{i,t} + \theta_i + e_{i,t} \qquad (3.2)\end{aligned}$$

where $\mathrm{CAR}_{i,t}[-5,+5]$ denotes the cumulative abnormal returns of firm i from five days before to five days after a natural disaster event. All returns are adjusted using contemporaneous returns for the FTSE All Share Index. The variable $D_{i,t}^{\text{Impacted}}$ is an indicator that equals one if a firm's location is in an affected area during the event date. Because natural disasters occur at different times and locations, treatment varies across firms and over time; our specification therefore captures within-firm changes in cumulative abnormal returns when a firm is impacted relative to periods when it is not. We consider alternative definitions of $D_{i,t}^{\text{Impacted}}$ to analyse how investors evaluate worldwide and domestic exposure to natural disasters. Based on the findings in Table A.3.2 and Table 3.2, we pay particular attention to the firm value implications of exposure at the headquarters level. Given the significant presence of *group*-level activities around parents' headquarters, as indicated in Table A.3.2, we expect investors to react more strongly to natural disasters that create uncertainty about firms' strategic operations. The idea that corporate headquarters capture strategic economic activity is further supported by our finding that natural disasters affecting these types of corporate locations are more likely to be reported in annual reports than those affecting subsidiaries (Table 3.2). The term $\mathbf{X}_{i,t}$ encompasses the same vector of control variables used by Nagar and Schoenfeld (2024), including log of total assets, book-to-market, ROA, and capital expenditures, thus allowing us to control for the characteristics underlying the five Fama–French factor model. The term θ_i represents firm fixed effects, which absorb time-invariant and potentially endogenous firm-level characteristics. We cluster standard errors at both the firm and year levels (Petersen, 2008).

The variable $D_{i,t-1}^{\text{High Exposure}}$ takes a value of one if a firm average of the physical climate risk ratio exceeds the sample average of the physical climate risk ratio over the year preceding a natural disaster event.[14] As explained in Nagar and Schoenfeld (2024), the $D_{i,t-1}^{\text{High Exposure}}$ variable has desirable properties to study how investors price physical climate risk disclosure at the firm level. First, differently from the lagged specification of the physical climate risk ratio, the dummy specification allows to capture firms that maintained high levels of climate risk disclosure over time. The variable thus identifies companies with long-term transparency practices about their climate risk exposure, which are likely to be of particular interest to investors during a natural disaster. Moreover, it also mitigates the concern of capturing extreme variation in the physical climate risk ratio that could be driven by reasons

[14]Differently from Nagar and Schoenfeld (2024), we use the climate-text sample *average* rather than the *median* sample average to compute $D_{i,t-1}^{\text{High Exposure}}$. Throughout the asset pricing tests, we prefer our approach because it is more conservative in the classification of firms with high levels of climate risk disclosure over time. However, we show that the response of cumulative abnormal returns to both specifications are similar.

other than physical climate risk exposure. Importantly, to allow market participants to process climate-related information, we assume the publication date of the annual report to be six months after the fiscal year-end.[15] To test if natural disaster events lead to negative returns for disaster-affected firms (Hypothesis H1A), the coefficients of interest in eq. (3.2) are given by β_1 and β_3, which capture the abnormal return impact of a natural disaster event on firms located in the affected area (β_1), and the differential return impact for affected firms that also disclose their climate risk exposure (β_3).

3.7 Results

This section presents our main empirical findings. We start with an event study to examine how investors price physical climate risk disclosure when natural disasters impact firm value. We then explore the possible channels behind these effects and test the robustness of our baseline findings.

3.7.1 Event Study

To better understand when investors consider the effects of information uncertainty material (Hypothesis H1A), we first analyse unconditional CARs, around natural disaster events affecting ADL1 or ADL2 areas worldwide or in the UK, averaged for both treatment and control firms. Table A.3.6 presents the results. Overall, the data reveals no statistical evidence to suggest that CARs are lower for companies located in ADL1 or ADL2 areas worldwide affected by natural disasters when compared to unaffected firms (see Panels A and B). Furthermore, in contrast to studies that examine the US equity market (Nagar and Schoenfeld, 2024), the findings in Panel C indicate that UK companies headquartered in domestic ADL1 areas affected by a natural

[15]We selected the six months limit in line with the legal deadline imposed to UK listed firms to release their annual reports. For more information, see: `https://www.lawfirmuk.net/accounting_e`

disaster do not face greater investor penalties in CARs than unaffected firms. However, this pattern changes significantly when analysing domestic ADL2 exposure to natural disasters, as shown by the abnormal return difference of 1.90% (t-value = -4.101) between impacted and not impacted firms (see Panel D). The results in Table A.3.6, Panel D, are also consistent with graphical evidence shown in Figure 3.3, which demonstrates a substantial decrease in CARs for impacted firms (solid line) versus a lower opposite movement for non-impacted firms (dashed line) when a natural disaster hit a firm's second administrative level location in the UK.

We next conduct multivariate regression analyses to control for more confounding factors. Table A.3.7 presents the results of eq. (3.2) when examining equity market responses to both foreign and domestic exposure to natural disasters. The estimated coefficient (β_1) for the term $D_{i,t}^{\text{Impacted}}$ in eq. (3.2) is similar whether we consider natural disaster impacts at the first administrative level (column (1)) or the second administrative level (column (3)). Consistent with the results in Table A.3.6 (Panels A and B), the findings indicate that there is no evidence to suggest that market-adjusted returns are lower for firms affected by natural disasters than for unaffected firms.

Table 3.3 presents the results focusing on natural disaster exposure at the headquarter level and, consistent with the evidence in Table A.3.6, Panel D and Figure 3.3, we find starkly different findings compared with previous analyses.[16] Specifically, while in Table 3.3, column (1), the sign of β_1 in eq. (3.2) is statistically insignificant (t-value = 0.570), in column (3) we find that firms affected by a natural disaster at the second administrative level in the UK exhibited a lower market-adjusted return of 200 bps relative to unaffected firms (t-value = -5.470). This effect is four times larger than that identified by Nagar and Schoenfeld (2024), who analysed the equity market

[16]In un-tabulated results, we also tested alternative specifications of the $D_{i,t}^{\text{Impacted}}$ variable to better isolate the effect of natural disaster exposure at either the foreign or domestic subsidiary level on CARs. However, we continued to find null results also in these tests. These results are available upon request.

responses of US firms headquartered in the state (the first administrative level in the US) hit by a natural disaster. To the best of our knowledge, we are not aware of any prior study documenting the impact of natural disasters on the stock returns of a large cross-section of UK listed firms.

In Table 3.3 we further control for the effects of climate risk disclosure on firm value. If physical climate risk disclosure harms firm value when natural disaster events occur, we would expect the coefficient (β_3) of the interaction term $D_{i,t}^{\text{Impacted}} * D_{i,t-1}^{\text{High Exposure}}$ in eq. (3.2) to be negative. Conversely, if investors positively evaluate physical climate risk disclosure in times of high information uncertainty, β_3 should be both positive and significant. Column (4) in Table 3.3 shows that β_3 is positive and statistically significant (t-value = 2.218). The estimate indicates that firms that disclose exposure to physical climate risks suffer a lower loss in value with respect to low disclosing firms when impacted by a natural disaster. Indeed, their market-adjusted returns recover from -220 basis points to -100 basis points as indicated by the sum of β_1 (-0.022) and β_3 (0.012). To ensure robustness, we repeat the estimation of eq. (3.2) by constructing the $D_{i,t-1}^{\text{High Exposure}}$ variable applying the methodology in Nagar and Schoenfeld (2024). In un-tabulated results, the estimated coefficient for β_3 remained positive and statistically significant under this specification (t-value = 2.482). Consistent with the notion that investors learn about physical climate risk disclosure only when the effects of natural disasters are considered value relevant, we do not find any statistical significance for the coefficient β_3 when analysing ADL1 domestic exposure (see column (2), Table 3.3). This result also holds when analysing worldwide exposure to natural disasters (see columns (2) and (4), Table A.3.7). Finally, these results cannot be driven by differences in size, value, profitability or physical asset investments between firms, as these factors are included as control variables. Moreover, by controlling for firm fixed effects, we ensure our firm value estimates are not driven by companies' time-invariant exposure to natural disasters. Based on the above findings, we focus our subsequent analyses on the firm-value implications of corporate headquarters exposure to natural disasters at the second administrative level in the UK.

3.7.2 Channels

This section aims to understand the underlying channels driving the results observed in the previous section, regarding the firm value implications of exposure to natural disasters and the relative effects of physical climate risk disclosure. Generally, a change in equity returns can be due to a change in expected cash flows, a change in uncertainty (discounting), or both (Liu et al., 2017). In the following subsections, we analyse each of these possibilities in detail.

Cash Flow Channel

One possible explanation for the differing equity return changes around natural disasters between firms with weak versus strong physical climate risk disclosure is a corresponding difference in expected cash flow changes (Hypothesis 2A). To analyse this possibility, we rely on changes in analysts' earnings forecasts before and after natural disaster realisations. Following Nagar and Schoenfeld (2024), we create an indicator variable, Downgrade_i, which equals one if, for the fiscal year-end after a natural disaster event, analysts revised their earnings per share (EPS) estimates downward one month after the event from one month before, and zero otherwise.[17] We estimated specifications similar to those in eq. (3.2), but replaced market-adjusted returns with the Downgrade_i variable. Table 3.4 presents the results in column (1). Overall, we find no significant evidence that analysts revise their EPS estimates downward for firms affected by natural disasters, regardless of their

[17] We considered the subsequent fiscal-year end and not the subsequent quarter-end as in Nagar and Schoenfeld (2024) given the low coverage of analysts' data in IBES at the quarter level for our sample. However, differently from Nagar and Schoenfeld (2024), we apply further analyses to evaluate the cash flow news hypothesis.

levels of physical climate risk disclosure.

We apply two further tests to investigate the robustness of these findings. First, apart from changes in expected cash flows, we employ *realised* cash flows as a proxy for changes in investors' expectations. This test is advantageous because it addresses the potential oversight of physical climate risks in cash flow evaluations by sell-side analysts (Han et al., 2024; Pankratz et al., 2023a). Second, we analysed the short-selling activity of institutional investors around natural disaster events. Given their greater ability to process climate risk information than retail investors (Choi et al., 2020), we would expect institutional investors, such as hedge funds, to engage in short-selling activities targeting stocks believed to have greater long-term exposure to natural disaster occurrences. However, it is also important to acknowledge the limitations associated with each of these tests. Regarding the former, realised cash flows contain look-ahead bias information (Liu et al., 2017). As for the latter, short-selling data are available only for part of our sample period, as the first short-selling observations have become available from 2012.[18] Despite these limitations, alignment of empirical evidence with the first two columns in Table 3.4 would further strengthen the lack of support for the cash-flow channel.

We measured the changes in *realised* cash flows by considering the change in ROA from the year before to after a natural disaster event (ΔROA_i). With respect to short-selling activity, we constructed a dummy variable, D_i^{Short}, which equals one when a company was subject to short-selling by an institutional investor within the [-5, +5] period around a natural disaster event. Table A.3.8 presents the results. Consistent with the findings in the first two columns of Table 3.4, the results in Table A.3.8 do not provide evidence of lower realised cash flows or heightened short-selling activities when firms are affected by natural disasters. In summary, the findings in the first column

[18] The reason underlying this lower coverage is that institutional investors were required to report all significant short positions only after the EU236 Rule. The EU236 Rule came into effect in November 2012.

of Table 3.4 and in Table A.3.8 tend to reject Hypothesis 2A (the cash flow channel hypothesis).

Stock Return Volatility Channel

Another plausible explanation for our findings in Table 3.3 may be that natural disasters cause an increase in information uncertainty at the firm level. We investigate the discount rate channel by considering two forms of investor uncertainty that could influence the premium dictated by information uncertainty, namely risk and ambiguity (Rehse et al., 2019). Risk is typically measured with stock return volatility (Liu et al., 2017; Rehse et al., 2019), while ambiguity is proxied with stock liquidity (Rehse et al., 2019). Epstein and Schneider (2008) note that investor uncertainty in the form of ambiguity aversion is entangled with, but different from, risk aversion dynamics. First, in the Epstein and Schneider (2008) model, stock return volatility influences not only risk premia but can also amplify ambiguity premia. However, what makes ambiguity premia different from risk premia is the first-order concern of ambiguity-averse investors with the *prospect* of low information quality about corporate fundamentals.[19] Therefore, in our empirical tests, we analyse both forms of investor uncertainty to discern better the relative impact of risk and ambiguity and ascertain which one contributes more significantly to driving the ambiguity premium around natural disaster events.

To examine changes in stock volatility, we adopt the approach outlined by Liu et al. (2017). Specifically, we computed a measure of abnormal volatility by calculating the percentage change in stock volatility from before to after a disaster event (ΔVol_i). Daily stock returns are used to construct volatility over a one-month post-disaster period. To account for seasonality, the

[19] More specifically, in the Epstein and Schneider (2008) model, ambiguity-averse investors require a premium for holding an asset simply because ambiguous information about that asset is expected to arrive. This result contrasts with the prediction of a Bayesian model with risk-adverse agents, in which variations in future information quality do not affect *current* utility and, consequently, current asset prices.

pre-natural disaster period was defined as the same calendar time window as the preceding year (Liu et al., 2017).[20] To test Hypothesis 2B, we estimated specifications similar to those in eq. (3.2) but replaced market-adjusted returns with the ΔVol_i variable.

Table 3.4 presents the results in column (2). The findings suggest no substantial change in risk for firms affected by a natural disaster. This result holds regardless of whether the impacted firm is a high- or low-disclosing company. Consequently, these outcomes tend to reject the possibility that our results are driven by increased risk aversion around natural disaster events.

Stock Liquidity Channel

Next, we assess whether the lower cumulative abnormal returns of low-disclosing firms compared to those disclosing only physical climate risks might be attributed to lower stock liquidity in the aftermath of a natural disaster event (Hypothesis 2B). Consistent with Rehse et al. (2019), we employed two measures of stock liquidity: daily trading volume in British pounds and bid-ask spreads. Moreover, as in Rehse et al. (2019), we computed daily bid-ask spreads following the approach proposed by Chung and Zhang (2014). To disentangle the impact of ambiguity from the risk-based explanation, we constructed measures of abnormal volume and spreads similar to the abnormal volatility measures described in the previous sub-section. Finally, we included abnormal volatility as a control when examining the relationship between natural disasters and stock liquidity. This approach enabled us to account for additional potential sources of confounding variation between stock liquidity and investors' ambiguity (Rehse et al., 2019).

[20]Differently from Liu et al. (2017), we employed one year, as opposed to two years, to establish the benchmark period, thereby preserving a greater number of observations for our analyses. Nonetheless, we also conducted tests using a reference period of two years, and this did not qualitatively change the conclusions of our findings.

Table 3.5 reports the results. Column (1) shows a highly statistically significant increase of 0.185% in daily closing spreads following a natural disaster event, especially for impacted low-disclosing firms. However, column (1) of Table 3.5 also indicates that impacted firms that disclose physical climate risks benefit from a *smaller* increase in closing spreads. Specifically, the coefficient for the interaction $D_{i,t}^{\text{Impacted}} * D_{i,t-1}^{\text{High Exposure}}$ reported in column (1) is -0.066 (t-value = -2.048). Furthermore, column (2) shows a 1.076% decrease in trading volume for low-disclosing firms impacted by a natural disaster. These results are significant at the 1% level. At the same time, column (2) in Table 3.5 also shows that natural disaster-affected firms that disclose physical climate risks benefit from a smaller decrease in trading volume. The result is significant at the 1% level.

In summary, the findings in Table 3.5 support the notion that the negative impact on the CAR of affected firms following a natural disaster might be driven by heightened investors' ambiguity caused by natural disasters. Our results also indicate that firm transparency about physical climate risks exposure can alleviate this ambiguity during times of high information uncertainty.

Further Cross-Sectional Evidence: Industry Competition

Finally, we carry out cross-sectional tests across two subsamples: firms operating in competitive industries and not competitive industries. We measure the level of market competition in each industry by calculating the Herfindahl-Hirschman Index (HHI) annually. Lower (higher) HHI scores indicate less (more) industry concentration and, consequently, higher (lower) market competition. Accordingly, a firm is considered to operate in a competitive environment in a given year if its industry's HHI falls below the median value of the HHI distribution calculated for that year (Ilhan et al., 2023a).

On the one hand, Ilhan et al. (2023a) explained that firm transparency about climate *risk* exposure could be "costly" in competitive industries, as this disclosure may reveal proprietary information to company's rivals.[21] On the other hand, Verrecchia (1983) argues that managers will disclose proprietary information when the increase in firm value resulting from disclosure outweighs the proprietary costs. In our context, if the benefits of corporate transparency about climate risk exposure occur in terms of reduced investors' uncertainty, we expect the effects of these benefits to be particularly evident in market environments where such transparency may be costly, yet value relevant for investors.

Table 3.6 reports the results of eq. (3.2) when using either CAR, closing spreads or trading volume as dependent variables for the subsamples of companies operating in no-competitive industries and the subsamples of companies operating in competitive industries. For the subsample of firms operating in no-competitive industries, columns (1), (3) and (5) show that the coefficient on the term $D_{i,t}^{\text{Impacted}}$ is always statistically significant (at least at the 5% level), while the same does not hold true for the coefficients on the double interactions terms involving the physical climate risk measures. On the other hand, for the subsample of firms operating in competitive industries, columns (2), (4) and (6) show a highly statistically significant coefficient on the term $D_{i,t}^{\text{Impacted}}$, as well as a statistically significant coefficient only for the double interaction term $D_{i,t}^{\text{Impacted}} * D_{i,t-1}^{\text{High Exposure}}$ in eq. (3.2). Overall, these findings suggest that the mild penalty in CAR documented in Table 3.6 is likely mainly driven by impacted firms disclosing physical climate risks in competitive industries.

[21] Examples of this proprietary information could include details about specific corporate operations impacted by natural disasters, as illustrated in Table A.3.5.

3.7.3 Robustness Tests

A potential concern regarding our baseline results is whether the fixed effect specification we have adopted in eq. (3.2) is appropriate for our staggered DID design (Baker et al., 2022). To address the validity of our setting, we applied two placebo tests, similar to those used by Nagar and Schoenfeld (2024). These placebo tests involved assigning two false dates to each natural disaster event, one 30 calendar days prior to the actual date and the other 30 days after. Results are presented in Table A.3.9 which shows no statistically significant results for the placebo tests. Therefore, these tests mitigate the possibility that our main results on physical climate risk disclosure in Table 3.5 are driven by endogeneity concerns and confirm the robustness of our findings.

Another issue with the interpretation of our baseline findings is that natural disasters may recur in the same locations. This may potentially influence the interpretation of the positive coefficient on $D_{i,t}^{\text{Impacted}} * D_{i,t-1}^{\text{High Exposure}}$ in eq. (3.2). In particular, if natural disasters tend to occur repeatedly in areas already identified as highly exposed, investors may anticipate such events and partially incorporate the associated risks into stock prices before a new natural disaster occurs. In this case, a less negative stock price decline following a natural disaster could reflect a lower degree of surprise rather than investor confidence in firms' transparency regarding physical climate risk exposure. To test this, we re-estimate eq. (3.2) separately for areas experiencing natural disaster exposure for the first time during our sample period and those affected more than once by natural disasters. Table A.3.10 reports the results. The results show that $D_{i,t}^{\text{Impacted}}$ is negative and statistically significant in both subsamples. However, the results in column 1 show that the magnitude of the effect is larger for firms impacted by a natural disaster for the first time. This finding is consistent with the notion that there is a stronger "surprise effect" following first-time natural disaster events. More importantly, the interaction term $D_{i,t}^{\text{Impacted}} * D_{i,t-1}^{\text{High Exposure}}$ is positive and statistically significant only for first-time natural disasters (see column 1), while it becomes smaller and less statistically significant for firms located in areas where natural disasters occur more frequently (see column 2). These findings suggest that the mitigating effect of disclosure on market reactions arises primarily when the natural disaster is unexpected and uncertainty is higher. When natural disasters recur multiple times in the same area, investors appear to have already priced in the risk, and the informational advantage of disclosure correspondingly declines. Overall, this evidence confirms that the positive coefficient on $D_{i,t}^{\text{Impacted}} * D_{i,t-1}^{\text{High Exposure}}$ in our baseline specification reflects the role of transparent physical risk disclosure in reducing uncertainty, rather than being driven by the predictability of recurrent natural disaster events.

3.8 Conclusions

This paper investigates how UK investors price firms' disclosures of physical climate risks. We use textual analysis from annual reports to identify high-disclosure firms and analyse market reactions to natural disasters as exogenous shocks to information uncertainty. We find that while UK firms headquartered in disaster-affected areas suffer significant negative abnormal returns, those that disclose physical climate risks experience substantially smaller losses in value. Our analysis shows these valuation effects are not driven by changes in cash flows or stock volatility but rather by improved stock liquidity, suggesting that disclosure reduces investor ambiguity after a natural disaster event. These results imply that greater transparency around physical climate risks can improve market efficiency and safeguard firm value.

Policy implications follow directly from our findings. As climate change continues to intensify physical risks, investors and regulators are increasingly demanding transparent reporting on firms' exposure and risk management strategies (Flammer et al., 2021). Our evidence suggests that encouraging disclosure of physical climate risks can enhance market efficiency and help safeguard firm value in the face of exogenous climate shocks. However, an important consideration is whether this positive effect of disclosure is driven by transparency regarding a firm's exposure to natural disasters, or by transparency about the measures taken to address such exposure. In the next chapter, we investigate these two dimensions to enable a better discussion of the benefits and costs of climate change disclosure for firm value.

3.9 Figures and Tables

Figure 3.1: Geographic Location and Exposure of UK Firm Headquarters and their Subsidiaries Worldwide. This figure shows the worldwide geographical distribution and exposure to natural disasters of UK firms in our sample. Panel A shows the location of UK parents' headquarters (in the UK) and their subsidiaries (in the UK or worldwide). Corporate ownership relationships were obtained from FAME, whereas firm location data were obtained from FAME, Dun & Bradstreet, and country-specific news websites. Panel B shows the first administrative levels worldwide where most UK firms were exposed to natural disasters either via their headquarters or their subsidiaries. We grouped first administrative levels worldwide into quartiles according to the number of UK companies affected by natural disasters in that area during the entire sample period. In this figure, a firm's location is considered affected if the first administrative division level worldwide where the company is located is hit by a natural disaster that costs at least £100 million in 2018 constant pounds. Natural disaster polygons were obtained from GDIS.

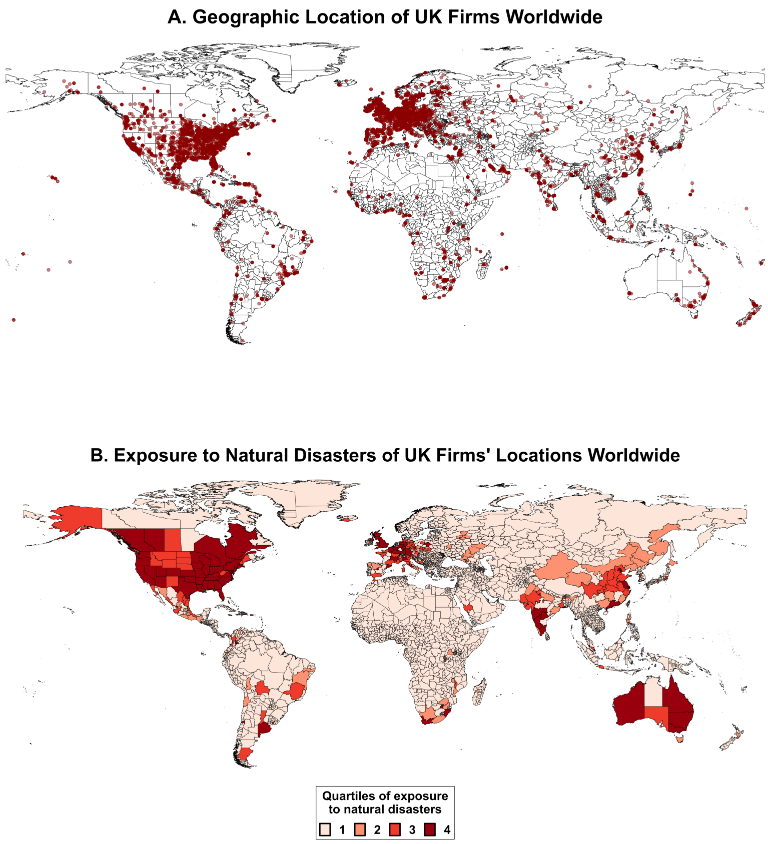


Figure 3.2: Geographic Location and Exposure of UK Firm Headquarters and their Subsidiaries in the UK. This figure shows the domestic geographical distribution and exposure to natural disasters of UK firms in our sample. Panel A shows the location of UK parents' headquarters and their subsidiaries in the UK. Corporate ownership relationships were obtained from FAME, whereas firm location data were obtained from FAME, Dun & Bradstreet, and country-specific news websites. Panel B shows the second administrative levels in the UK where most UK firms were exposed to natural disasters either via their headquarters or their subsidiaries. We grouped second administrative levels in the UK into quartiles according to the number of UK companies affected by natural disasters in that area during the entire sample period. In this figure, a firm's location is considered affected if the second administrative division level in the UK where the company is located is hit by a natural disaster that costs at least £100 million in 2018 constant pounds. Natural disaster polygons were obtained from GDIS.

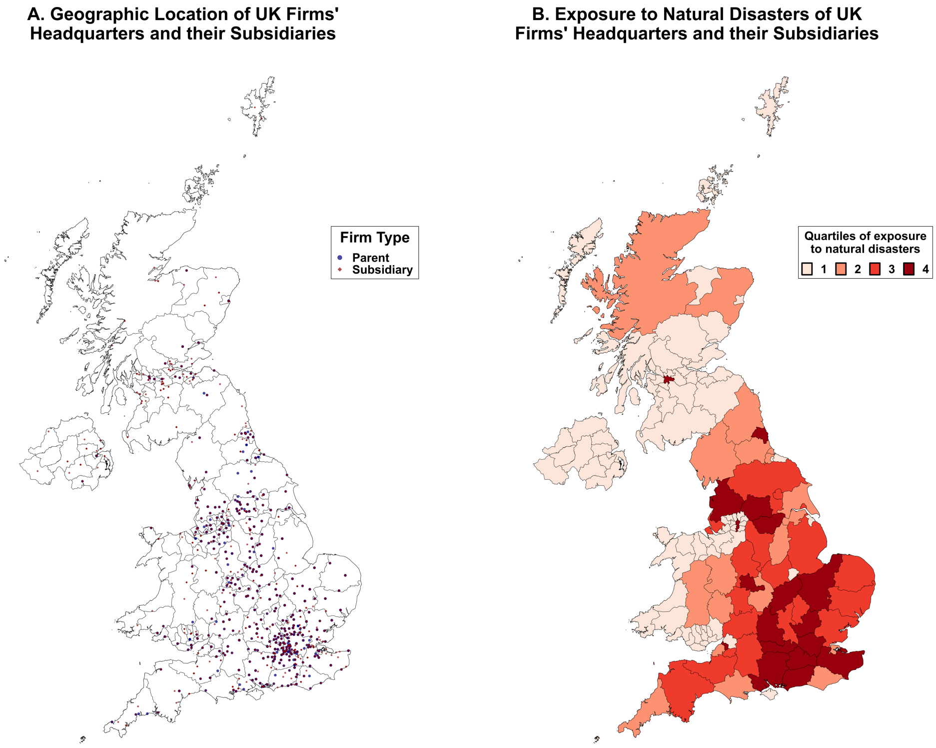


Figure 3.3: Cumulative Abnormal returns around natural disaster events. This figure shows the daily average cumulative market-adjusted returns of U.K. firms around natural disasters dates. For this analysis, we retained only natural disasters that met each of the following criteria: (i) their duration was less than 30 days, and (ii) they caused at least £100 million in damage, as reported by EM-DAT (in 2018 CPI-adjusted values). In this figure, we define a company as impacted if its headquarter was located in an area affected by a natural disaster on a given date at the second administrative level in the UK. Impacted firms are represented by the solid line. Not impacted firms are represented by the dashed-dotted line. Table A.3.1 defines all variables in detail.

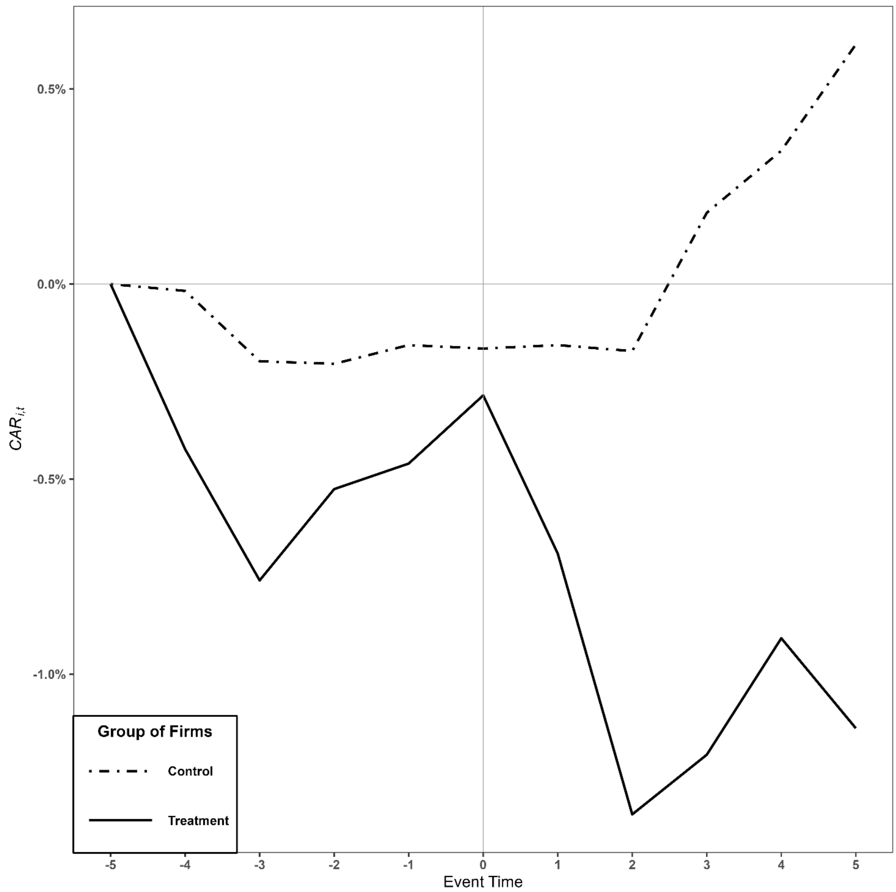


Table 3.1: Summary Statistics. This table reports the summary statistics for the variables used in this study. Textual data was retrieved from Thomson Reuters DataStream and Companies House. Financial data was obtained data from Worldscope, FAME, and Compustat Global. Natural disaster data was obtained by spatially merging information from FAME and GDIS. Our initial sample includes all non-financial firms listed on the London Stock Exchange from 1996 to 2018. All continuous variables were winsorised at the 1% and 99% levels. Table A.3.1 provides detailed variable definitions.

Variable	**N**	**Mean**	**S.D.**	**p25**	**Median**	**p75**
$TM^{High\ Exposure}$	22,542	0.067	0.164	0	0	0.056
$\log(TA)$	22,542	11.202	2.174	9.715	11.022	12.558
PPE	22,542	0.266	0.256	0.053	0.184	0.407
ROA	22,542	-0.050	0.318	-0.040	0.035	0.079
$CapEx$	22,542	0.049	0.057	0.012	0.031	0.064
$Leverage$	22,542	0.192	0.206	0.019	0.148	0.288
$D^{Impacted(ADL1)}$	22,542	0.459	0.498	0	0	1
$D^{Impacted(ADL2)}$	22,542	0.126	0.332	0	0	1
$D^{Impacted(HQ,\ ADL1)}$	22,542	0.333	0.471	0	0	1
$D^{Impacted(HQ,\ ADL2)}$	22,542	0.056	0.230	0	0	0

Table 3.2: Validation of the physical climate risk measure. This table examines whether natural disasters affected the physical climate risk text measure of impacted firms relative to non-impacted firms from 1996 to 2018. In all columns, the dependent variable is the normalised physical climate risk ratio ($\text{TM}_{i,t}^{\text{High Exposure}}$). In columns (1) and (4), a firm is considered to be impacted if either its headquarters or one of its subsidiaries is located in an area affected by a natural disaster in a given year ($D_{i,t}^{\text{Impacted}}$). In columns (2) and (4), a firm is considered affected if its headquarter is located in an area affected by a natural disaster in a given year ($D_{i,t}^{Impacted\ (HQ)}$), or if only one of its subsidiaries is located in an area affected by a natural disaster in a given year ($D_{i,t}^{Impacted\ (Subs.)}$). In columns (3) and (6), a firm is considered affected if its headquarter is located in an area affected by a natural disaster in a given year ($D_{i,t}^{Impacted\ (HQ)}$), or if only one of its domestic subsidiaries is located in an area affected by a natural disaster in a given year ($D_{i,t}^{Impacted\ (UK\ Subs.)}$), or if only one of its foreign subsidiaries is located in an area affected by a natural disaster in a given year ($D_{i,t}^{Impacted\ (No\ UK\ Subs.)}$). In columns (1)-(3), we define an area affected if a natural disaster happened in one of the first-level administrative divisions (ADL1). In columns (4)-(6), we define an area affected if a natural disaster happened in one of the second-level administrative divisions (ADL2). Log (TA), PPE, CapEx, Leverage and ROA. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.3.1 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	$TM^{High\ Exposure}$					
Detail of Affected Area:	**ADL1**			**ADL2**		
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
$D_{i,t}^{Impacted}$	0.007***			0.008***		
	(2.093)			(2.832)		
$D_{i,t}^{Impacted(HQ)}$		0.010***	0.010***		0.011***	0.011***
		(3.812)	(3.654)		(2.996)	(2.917)
$D_{i,t}^{Impacted(Subs.)}$		0.001			0.002	
		(0.363)			(0.586)	
$D_{i,t}^{Impacted(UKSubs.)}$			-0.031			0.007
			(-1.543)			(0.677)
$D_{i,t}^{Impacted(NoUKSubs.)}$			0.004			0.001
			(1.117)			(0.288)
$\log(TA)_{i,t}$	0.007***	0.007***	0.007***	0.007***	0.007***	0.008***
	(3.024)	(3.040)	(2.977)	(3.087)	(3.092)	(3.100)
$PPE_{i,t}$	0.032**	0.032**	0.032**	0.032**	0.032**	0.032**
	(2.082)	(2.068)	(2.054)	(2.093)	(2.090)	(2.087)
$CapEx_{i,t}$	0.030	0.029	0.030	0.029	0.029	0.029
	(1.103)	(1.096)	(1.105)	(1.095)	(1.083)	(1.097)
$Leverage_{i,t}$	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(-0.497)	(-0.496)	(-0.504)	(-0.514)	(-0.491)	(-0.494)
$ROA_{i,t}$	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.238)	(-0.278)	(-0.251)	(-0.254)	(-0.275)	(-0.278)
Obs.	22,542	22,542	22,542	22,542	22,542	22,542
R^2 Adj.	0.513	0.514	0.514	0.513	0.513	0.513
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 3.3: Reaction of market-adjusted returns to natural disasters from 1996 to 2018 (Domestic exposure). This table examines UK stock market's reaction to natural disasters at the firm level. For this analysis, we retained only natural disasters that met each of the following criteria: (i) their duration was less than 30 days, and (ii) they caused at least £100 million in damage, as reported by EM-DAT (in 2018 CPI-adjusted values). We define a firm as treated if its headquarter is located in an area affected by a natural disaster on a given date. In columns (1) and (2), we define an area affected if a natural disaster happened in one of the first-level administrative divisions in the UK (ADL1). In columns (3) and (4), we define an area affected if a natural disaster happened in one of the second-level administrative divisions in the UK (ADL2). In all columns, the dependent variable is the cumulative market-adjusted returns for the treatment and control firms from five days before to five days after the natural disaster event, $\text{CAR}_{i,t}[-5,+5]$. All returns are adjusted using contemporaneous returns for the FTSE All Share Index. In columns (2) and (4), $D_{i,t-1}^{\text{High Exposure}}$ takes the value of one if the firm physical climate-text average is greater than the sample physical climate-text average the year before a natural disaster event. Firm-level control variables include Log (TA), B/M, ROA and CapEx. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.3.1 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	$CAR_{i,t}[-5,+5]$			
Detail of Affected Area (UK):	**ADL1**		**ADL2**	
Specification:	(1)	(2)	(3)	(4)
$D_{i,t}^{Impacted(HQ)}$	0.006	0.006	-0.020***	-0.023***
	(0.570)	(0.502)	(-5.470)	(-5.018)
$D_{i,t-1}^{High\,Exposure}$		-0.010		0.003
		(-0.957)		(0.880)
$D_{i,t}^{Impacted(HQ)} \times D_{i,t-1}^{High\,Exposure}$		0.001		0.012**
		(0.314)		(2.218)
$\log(TA)_{i,t}$	-0.002	-0.002	-0.002	-0.002
	(-0.492)	(-0.516)	(-0.501)	(-0.517)
$B/M_{i,t}$	-0.013***	-0.013***	-0.012***	-0.012***
	(-4.590)	(-4.560)	(-4.572)	(-4.588)
$ROA_{i,t}$	0.029***	0.029***	0.029***	0.029***
	(3.593)	(3.597)	(3.690)	(3.715)
$CapEx_{i,t}$	-0.064*	-0.064*	-0.060**	-0.060**
	(-1.971)	(-1.966)	(-2.052)	(-2.047)
Obs.	11,535	11,535	11,535	11,535
R^2 Adj.	0.029	0.029	0.029	0.030
Firm FE	YES	YES	YES	YES

Table 3.4: Expected cash flows and volatility change analysis around natural disaster events in the UK. This table reports the effect of natural disasters occurring in the UK at the second administrative level on the change in analysts' earnings per share (EPS) forecasts and daily stock return volatility. Details of the event studies are presented in Table 3.3. In all columns, we define a firm as treated if its headquarter is located in a second administrative area affected by a natural disaster on a given date in the UK. In column (1), the dependent variable Downgrade_i equals one if the mean consensus in forecasted EPS for the fiscal-year end when a natural disaster happened decreases from 20 trading days before to 20 trading days after a natural disaster, and zero otherwise. In column (2), the dependent variable is the percentage change in daily stock return volatility from before to after a natural disaster event, denoted $\Delta\text{Vol}_{i,t}$. The post-event period was defined as one month after a natural disaster event, and the pre-event period was defined as the same post-event period one year before the event. In both columns, $D^{\text{High Exposure}}_{i,t-1}$ takes the value of one if the firm physical climate-text average is greater than the sample physical climate-text average the year before a natural disaster event. Firm-level control variables include Log (TA), B/M, ROA, and CapEx. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.3.1 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	$Downgrade_i$	$\Delta\,Vol_i$
Detail of Affected Area (UK): *ADL2*		
Specification:	(1)	(2)
$D^{\text{Impacted(HQ)}}_{it}$	0.003	-0.019
	(0.151)	(-0.225)
$D^{\text{High Exposure}}_{it-1}$	-0.028	0.025
	(-0.824)	(0.347)
$D^{\text{Impacted(HQ)}}_{it} \times D^{\text{High Exposure}}_{it-1}$	-0.002	-0.050
	(-0.042)	(-0.456)
$\log(TA)_{i,t}$	0.116***	-0.040
	(6.295)	(-1.046)
$B/M_{i,t}$	0.041**	0.034
	(2.295)	(0.485)
$ROA_{i,t}$	-0.242***	-0.187
	(-3.931)	(-1.163)
$CapEx_{i,t}$	0.408**	1.988***
	(2.136)	(3.439)
Obs.	8,307	11,000
R^2 Adj.	0.142	0.149
Controls	YES	YES
Firm FE	YES	YES

Table 3.5: Regression results of daily closing spread and trading volume changes around natural disaster events in the UK. This table reports the effect of natural disasters occurring in the UK at the second administrative level on daily closing spreads and daily trading volume. Details of the event studies are presented in Table 3.3. In all columns, we define a firm as treated if its headquarter is located in a second administrative area affected by a natural disaster on a given date in the UK. In column (1), the dependent variable is the change in closing spread from before to after a natural disaster event, expressed as a percentage. Closing spreads are calculated as in Chung & Zhang (2014). In column (2), the dependent variable is the change in British-pound trading volume from before to after a natural disaster event, also expressed as a percentage. In all columns, the post-event period is defined as one month after a natural disaster event, and the pre-event period is defined as the same post-event period one year before the event. In both columns, $D_{i,t-1}^{\text{High Exposure}}$ takes the value of one if the firm physical climate-text average is greater than the sample physical climate-text average the year before a natural disaster event. Firm-level control variables include Log (TA), B/M, ROA, CapEx, and ΔVol_i. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.3.1 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ΔClosing Spread$_i$	ΔTrading Volume$_i$
Detail of Affected Area (UK): *ADL2*		
Specification:	(1)	(2)
$D_{it}^{\text{Impacted(HQ)}}$	0.185***	-1.349***
	(3.049)	(-3.992)
$D_{it-1}^{\text{High Exposure}}$	-0.055	-0.848
	(-0.805)	(-1.152)
$D_{it}^{\text{Impacted(HQ)}} \times D_{it-1}^{\text{High Exposure}}$	-0.066**	1.084***
	(-2.048)	(2.621)
$\log(TA)_{i,t}$	0.006	-1.013***
	(0.210)	(-4.095)
$B/M_{i,t}$	0.223***	-0.979***
	(4.247)	(-4.698)
$ROA_{i,t}$	-0.577***	4.404***
	(-5.507)	(3.201)
$CapEx_{i,t}$	0.954*	1.030
	(1.871)	(0.170)
Obs.	11,000	10,944
R^2 Adj.	0.202	0.212
Volatility Control	YES	YES
Firm FE	YES	YES

Table 3.6: Regression results of market-adjusted returns, daily closing spread and trading volume changes around natural disaster events in the UK, split by industry competition. This table reports the effect of natural disasters occurring in the UK at the second administrative level on market-adjusted returns, daily closing spreads, and daily trading volume for firms operating in competitive and non-competitive industries separately. Details of the event studies are presented in Table 3.3. In columns (1) and (2), the dependent variable is the cumulative market-adjusted returns for the treatment and control firms from five days before to five days after the natural disaster event ($\text{CAR}_{i,t}[-5,+5]$). In columns (3) and (4), the dependent variable is the change in closing spread from before to after a natural disaster event in percentage. Closing spread are calculated as in Chung and Zhang (2014). In columns (5) and (6), the dependent variable is the change in British-pound trading volume from before to after a natural disaster event in percentage. Columns (1), (3) and (5) report the results for firms operating in not-competitive industries. Columns (2), (4) and (6) report the results for firms operating in competitive industries. A firm is considered to operate in a competitive (not-competitive) environment in a given year if its industry's HHI falls below (above) the median value of the HHI distribution calculated for that year. In all columns, $D_{i,t-1}^{\text{High Exposure}}$ takes the value of one if the firm physical climate-text average is greater than the sample physical climate-text average the year before a natural disaster event. In all columns, firm-level control variables include Log (TA), B/M, ROA, CapEx. Columns (3)-(6) also include ΔVol_i. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.3.1 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	$CAR_{i,t}[-5,+5]$		ΔClosing Spread$_i$		ΔTrading Volume$_i$	
Detail of Affected Area (UK): *ADL2*						
Type of Industry:	Not Competitive	Competitive	Not Competitive	Competitive	Not Competitive	Competitive
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
$D_{i,t}^{Impacted(HQ)}$	-0.019***	-0.024***	0.041	0.215**	-1.730*	-1.294***
	(-2.603)	(-4.767)	(0.794)	(3.109)	(-1.798)	(-3.070)
$D_{i,t-1}^{HighExposure}$	-0.009	0.006	0.002	-0.068	-4.207	0.184
	(-0.707)	(1.207)	(0.031	(-0.845)	(-1.488)	(0.267)
$D_{i,t}^{Impacted(HQ)} \times D_{i,t-1}^{HighExposure}$	0.001	0.015***	0.015	-0.083**	2.604	0.576**
	(0.068)	(2.765)	(0.221)	(-2.140)	(1.456)	(2.052)
Obs.	2,670	8,265	2,560	8,440	2,434	7,660
R2 Adj.	0.005	0.038	0.228	0.197	0.280	0.137
Controls	YES	YES	YES	YES	YES	YES
Volatility Control	NO	NO	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

3.10 Appendix

3.10.1 Converting UK financial reports into a readable format

In this Appendix, we explain the procedure we followed to convert the sample of UK financial reports into machine-readable documents. As outlined in Section 3.4.1 of the main article, we collect UK financial reports data from both Thomson Reuters Eikon and Companies House. To the best of our knowledge, our sample represents the largest dataset of corporate annual reports of UK listed firms.

In Thomson Reuters Eikon, PDF files for UK financial reports are provided in one of the following formats: (i) digitally created PDFs, (ii) semi-scanned PDFs, or (iii) fully scanned PDFs. In contrast, Companies House provides only fully scanned PDFs files. Therefore, we developed an algorithm capable of identifying each of these cases with full accuracy. For digitally created PDF files, we utilised text-mining modules in Python to extract text from annual reports. For semi-scanned and fully scanned PDF files, we employed Optical Character Recognition (OCR) algorithms to convert the files into digital formats.

Importantly, to ensure the highest quality of the textual sources, we applied text pre-processing techniques such as binarisation and skew correction when processing semi-scanned or fully scanned PDF files. These techniques are aimed at enhancing the accuracy of OCR algorithms.[22]

[22]For further information about text-preprocess techniques, see: https://nextgeninvent.com/blogs/7-steps-of-image-pre-processing-to-improve-ocr-using-python-2/

3.10.2 Additional Tables

Table A.3.1: Variable Definitions. This table describes the variables used in our analyses and their respective sources. Data sources are: CG = Compustat Global; CH = Companies House; DS = Thomson Reuters DataStream; F = FAME; G = GDIS; IBES = Institutional Brokers' Estimate System; R = Refinitiv; TRE = Thomson Reuters Eikon; W = Worldscope; WS = WRDS European Short Data.

Variable	**Definition and Sources**
$TM^{High\,Exposure}$	The frequency of unigrams or bigrams related to our physical climate risk dictionary in a generic annual report, divided by the number of words in the annual report. (Sources: TRE, CH).
$D^{High\,Exposure}$	A dummy variable taking the value of one if the firm average value for $TM^{High\,Exposure}$ is greater than the sample average value. (Sources: TRE, CH).
$D^{Impacted}$	A dummy taking the value of one if either the firm headquarter or one of its subsidiaries is located in an affected area worldwide at a given time. (Sources: F, G).
$D^{Impacted(HQ)}$	A dummy taking the value of one if the firm headquarter is located in an affected area in the UK at a given time. (Sources: F, G).
$D^{Impacted(Subs)}$	A dummy taking the value of one if a firm subsidiary is located in an affected area worldwide at a given time. (Sources: F, G).
$D^{Impacted(UKSubs.)}$	A dummy taking the value of one if only one of a firm subsidiary is located in an affected area in the UK at a given time. (Sources: F, G).

Variable	Definition and Sources
$D^{Impacted(NoUKSubs.)}$	A dummy taking the value of one if only one of a firm subsidiary is located in an affected area outside the UK at a given time. (Sources: F, G).
CAR[-5,+5]	Cumulative market-adjusted returns for treatment and control firms from five days before to five days after the natural disaster event. (Sources: DS).
Δ*Closing Spread*	The difference in bid-ask spreads in percentage over a one-month period following a natural disaster event and during the same calendar time window in the previous year. (Sources: DS).
Δ*Trading Volume*	The difference in British-pound trading volume in percentage over a one-month period following a natural disaster event and during the same calendar time window in the previous year. (Sources: DS).
Δ*Vol*	The difference in volatility of daily stock returns in percentage over a one-month period following a natural disaster event and during the same calendar time window in the previous year. (Sources: DS).
Downgrade	A dummy variable taking the value of one if the mean consensus in forecasted EPS for the fiscal-year end when a natural disaster happened decreases from 20 trading days before to 20 trading days after a natural disaster. (Sources: IBES).
ΔROA	The change in net income divided by total assets from the year before to one year after a natural disaster. (Sources: W, F, CG).

Variable	Definition and Sources
D^{Short}	A dummy variable taking the value of one if at least one institutional investor short-sells a firm from five days before to five days after the natural disaster event. (Sources: WS).
Log(TA)	Natural logarithm of firm's total assets. (Sources: W, F, CG).
PPE/TA	Property, plant and equipment, divided by total assets of the same year. (Sources: W, F, CG).
B/M	Book value of shareholder equity, divided by the market capitalisation at the end of the fiscal year. (Sources: W, F, CG).
ROA	Net income, divided by total assets of the same year. (Sources: W, F, CG).
CapEx	Capital Expenditures, divided by total assets of the same year. (Sources: W, F, CG).
Leverage	Total debt (short-term debt and long-term debt), divided by the total asset. (Sources: W, F, CG).
R&D	Research and development expenditures, divided by total assets of the same year. (Sources: W, F, CG).

Table A.3.2: Summary Statistics about Firm Parent Ownership and Corporate Locations. This table presents summary statistics about the corporate ownership distribution of parent firms in our sample. We distinguish between parent firms with a single location ("Only headquarters (HQ)"), those with subsidiaries exclusively in the UK ("HQ and only UK subsidiaries"), and those with at least one foreign subsidiary ("HQ and at least one foreign subsidiary"). Panel A reports information about the number of corporate locations within the corporate group. Panel B reports the distance, measured in kilometres, of corporate subsidiaries from the location of the parent's headquarters. Corporate ownership and location data were obtained from FAME. Our initial sample includes all non-financial firms listed on the London Stock Exchange from 1996–2018. Table A.3.1 provides detailed variable definitions.

Firm Parent Ownership	**N**	**Mean**	**S.D.**	**p25**	**Median**	**p75**
Panel A. Number of Corporate Locations						
Only headquarter (HQ)	920	1	0	1	1	1
HQ and only UK subsidiaries	710	8	18	2	4	7
HQ and at least one foreign subsidiary	929	41	88	5	11	33
Panel B. Distance (in kilometres) between HQ and Subsidiaries locations						
HQ and only UK subsidiaries	710	39	110	0	0	0
HQ and at least one foreign subsidiary	929	3521	4374	0	721	6735

Table A.3.3: Top-100 climate-related keywords across annual reports. This table reports the top 100 unigrams or bigrams associated with $TM^{\text{High Exposure}}$. Table A.3.1 defines all variables in detail.

Unigram/Bigram	N	Unigram/Bigram	N	Unigram/Bigram	N
weather	9730	of hurricane	80	the rain	48
temperature	4404	storms in	76	dry summer	47
flooding	1711	of storm	74	the rainy	47
temperatures	1273	soil erosion	71	flood damage	46
rainfall	1191	hurricanes in	71	of rain	46
drought	755	winter conditions	68	perfect storm	46
floods	493	of flood	67	unseasonably warm	45
subsidence	259	hurricanes and	66	of snow	45
poor summer	221	for typhoon	64	wetter	44
the storm	194	coldest	62	snowfall	44
the flood	194	storm damage	62	storm of	43
mild winter	184	hurricane season	61	to flood	43
storm and	167	droughts	61	exceptionally cold	43
hot summer	163	rains and	61	hurricane sandy	41
typhoon and	154	by hurricane	61	the storms	41
the typhoon	149	storm costs	60	very wet	41
colder	148	flood at	59	exceptionally hot	41
flood risk	142	wet summer	59	very hot	41
severe winter	138	snow in	59	dry season	40
and flood	124	rainy season	59	by lightning	40
wettest	116	heavy rains	58	very warm	40
cold winter	112	heavy rain	55	cold season	40
unseasonal	105	flood or	54	very cold	39
major storms	100	as hurricanes	54	storm in	39
hurricane katrina	98	and snow	52	rain and	39
flood and	97	water flood	52	rock falls	39
the snow	93	extreme cold	51	and rain	39
snow and	87	hurricane harvey	51	tornado and	38
dry periods	87	wet season	50	heating season	38
of typhoon	84	dry conditions	50	or flood	37
and storm	83	the hurricanes	50	heavy snow	37
lightning strikes	82	storms and	49	wildfires	36
the hurricane	81	harsh winter	48	and tornado	36
the tornado	81				

Table A.3.4: Industry patterns of the physical climate risk measure. This table reports firms' physical climate risk for the top 10 industries. Statistics are reported at the firm-year level across different supersectors according to the ICB classification system. $\text{TM}^{\text{High Exposure}}$ measures the relative frequency of unigrams or bigrams related to our physical climate risk dictionary in a firm's annual report.

Supersector (ICB)	**Mean**	**S.D.**	**N**
Utilities	0.329	0.334	382
Food, Beverage and Tobacco	0.218	0.308	233
Chemicals	0.134	0.222	412
Basic Resources	0.110	0.170	438
Energy	0.103	0.169	1036
Construction and Materials	0.100	0.169	833
Travel and Leisure	0.088	0.138	1662
Industrial Goods and Services	0.080	0.164	5307
Retail	0.059	0.143	1262
Personal Care, Drug and Grocery Stores	0.054	0.117	387

Table A.3.5: Excerpts in UK annual reports with the highest physical climate risk measures. This table presents excerpts from UK annual reports with the highest values of the physical climate risk measures. These excerpts are text fragments extracted from the portion of each annual report where the algorithm identifies the discussion of physical climate risk keywords. Physical climate risk keywords are highlighted in *bold*. We also report the year of the annual report and the firm's industry affiliation according to the ICB classification system.

Firm	**Supersector**	**Year**	**Text surrounding physical climate risk keywords (bold)**
National Grid PLC	Energy	2016	In the US, we did not achieve our targets. Customers were again concerned about higher-than-normal winter bills as a result of electricity commodity price increases and higher gas usage due to cold **weather**. In an effort to rebuild trust and customer satisfaction, we put in place a customer outreach and education programme similar to last year that focused on energy-saving solutions and bill management.
United Utilities Group PLC	Utilities	2016	December 2015 will be remembered as an awful time for many customers in Cumbria, Lancashire and Greater Manchester when communities were inundated by **flooding** caused by unprecedented rainfall (see case study, page 35). The **storms** at the beginning of December affected over 85 of our wastewater treatment works and a number of other facilities. Dealing with the earlier water quality incident had heightened our readiness.
Anglo-Eastern Plantations PLC	Food, Beverage and Tobacco	2018	Dry periods, in particular, will affect yields in the short and medium term. **Drought** induces moisture stress in palm trees. High levels of **rainfall** can disrupt estate operations and result in harvesting delays with loss of FFB or deterioration in fruit quality.
Invista Real Estate PLC	Construction and Materials	2007	We believe that through the implementation of this programme we will be able to manage effectively our sustainability-related risks associated with, for example, climate change (more severe and regular **flooding**, increasing **storm damage** costs and rising energy prices).

Table A.3.6: Univariate tests of unconditional cumulative abnormal returns around natural disaster events. This table shows the daily average cumulative abnormal returns of UK firms around natural disaster event dates. $\text{CAR}_{i,t}[-5,+5]$ is the cumulative market-adjusted return for impacted and non-impacted firms from five days before to five days after the natural disaster event. For this analysis, we retained only natural disasters that met each of the following criteria: (i) their duration was less than 30 days, and (ii) they caused at least £100 million in damage, as reported by EM-DAT (in 2018 CPI-adjusted values). In Panel A (Panel B), we define a company as impacted if either its headquarters or one of its subsidiaries was located in an area affected by a natural disaster on a given date at the first (second) administrative level worldwide. In Panel C (Panel D), a company is considered impacted if its headquarters was located in an area affected by a natural disaster at the first (second) administrative level in the UK. We winsorised the $\text{CAR}_{i,t}[-5,+5]$ variable at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.3.1 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Group of firms	**Not Impacted (A)**	**Impacted (B)**	**(B) minus (A)**
Panel A: Natural disasters affecting ADL1 areas worldwide			
$CAR_{i,t}$[-5, +5]	-0.006	-0.000	0.006
			(1.356)
Panel B: Natural disasters affecting ADL2 areas worldwide			
$CAR_{i,t}$[-5, +5]	-0.005	-0.004	0.001
			(0.112)
Panel C: Natural disasters affecting ADL1 areas in the UK			
$CAR_{i,t}$[-5, +5]	0.009	0.003	-0.006
			(-1.215)
Panel D: Natural disasters affecting ADL2 areas in the UK			
$CAR_{i,t}$[-5, +5]	0.006	-0.013	**-0.019*** **
			(-4.101)

Table A.3.7: Market-adjusted returns to natural disasters from 1996 to 2018 (Worldwide Exposure). This table examines the UK stock market's reaction to natural disasters at the firm level. For this analysis, we retained only natural disasters that met each of the following criteria: (i) their duration was less than 30 days, and (ii) they caused at least £100 million in damage, as reported by EM-DAT (in 2018 CPI-adjusted values). We define a firm as treated if either its headquarters or one of its subsidiaries was located in an affected area on a given date. In columns (1) and (2), an area is defined as affected if a natural disaster occurred in one of the first-level administrative divisions worldwide. In columns (3) and (4), an area is considered affected if the disaster occurred in one of the second-level administrative divisions worldwide. In all columns, the dependent variable is the cumulative market-adjusted return over the $[-5,+5]$ event window, denoted $\mathrm{CAR}_{i,t}[-5,+5]$. All returns are adjusted using contemporaneous returns from the FTSE All Share Index. Firm-level control variables include Log (TA), B/M, ROA, and CapEx. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.3.1 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	$CAR_{i,t}[-5,+5]$			
Specification:	(1)	(2)	(3)	(4)
$D_{i,t}^{\text{Impacted}}$	0.003	0.002	-0.003	-0.004
	(0.529)	(0.424)	(-0.725)	(-0.807)
$D_{i,t-1}^{\text{High Exposure}}$		0.000		0.001
		(0.415)		(0.570)
$D_{i,t}^{\text{Impacted}} \times D_{i,t-1}^{\text{High Exposure}}$		0.001		0.003
		(0.393)		(0.766)
$\log(\mathrm{TA})_{i,t}$	-0.003***	-0.003***	-0.003***	-0.003***
	(-2.843)	(-2.843)	(-2.801)	(-2.807)
$B/M_{i,t}$	-0.008***	-0.008***	-0.008***	-0.008***
	(-7.368)	(-7.357)	(-7.192)	(-7.184)
$ROA_{i,t}$	0.019***	0.019***	0.018***	0.018***
	(6.639)	(6.657)	(6.304)	(6.320)
$CapEx_{i,t}$	-0.028***	-0.028***	-0.030***	-0.030***
	(-2.607)	(-2.608)	(-2.660)	(-2.662)
Obs.	137,357	137,357	137,357	137,357
R^2 Adj.	0.020	0.020	0.019	0.019
Firm FE	YES	YES	YES	YES

Table A.3.8: Realized cash flows and short-selling activity analysis around natural disaster events in the UK. This table reports the effect of natural disasters in the UK at the second administrative level on firms' future accounting performance and the short-selling activity of institutional investors. In column (1), the dependent variable is the change in earnings divided by total assets from the year before to one year after a natural disaster, denoted ΔROA_i. In column (2), the dependent variable $D^{\text{Short}}_{i,t}$ equals one if at least one institutional investor short-sells a firm during the $[-5, +5]$ window. In columns (1) and (2), $D^{\text{High Exposure}}_{i,t-1}$ takes the value of one if the firm physical climate-text average is greater than the sample physical climate-text average the year before a natural disaster event. In column (1), firm-level control variables include Log (TA), B/M, and CapEx. In column (2), control variables include Log (TA), ROA, B/M, and CapEx. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.3.1 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ΔROA_i	D^{Short}_i
Specification:	(1)	(2)
$D^{\text{Impacted}}_{i,t}$	-0.006	-0.439*
	(-1.005)	(-2.509)
$D^{\text{High Exposure}}_{i,t-1}$	-0.003	-0.018
	(-0.297)	(-0.890)
$D^{\text{Impacted}}_{i,t} \times D^{\text{High Exposure}}_{i,t-1}$	0.007	-0.008
	(0.728)	(-0.146)
$\log(\text{TA})_{i,t}$	-0.013	0.060**
	(-1.642)	(3.971)
$B/M_{i,t}$	-0.018***	0.025
	(-3.711)	(1.732)
$CapEx_{i,t}$	-0.391***	-0.052
	(-5.479)	(-1.791)
Obs.	11,277	2,308
R^2 Adj.	0.334	0.422
Controls	YES	YES
ROA Control	NO	YES
Firm FE	YES	YES

Table A.3.9: Placebo Tests. This table examines stock market reactions to two placebo dates for natural disasters that occurred at the second-level administrative division in the UK. In all columns, the dependent variable is the cumulative market-adjusted return for treatment and control firms over the $[-5, +5]$ period. In column (1), we assign a false disaster date 30 calendar days before the actual event. In column (2), the false date is set 30 calendar days after the true event. In columns (1) and (2), $D_{i,t-1}^{\text{High Exposure}}$ takes the value of one if the firm physical climate-text average is greater than the sample physical climate-text average the year before a natural disaster event. Firm-level control variables include Log (TA), B/M, ROA, and CapEx. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.3.1 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	$CAR_{i,t}[-5, +5]$	
Placebo Dates:	30 days before the event	30 days after the event
Specification:	(1)	(2)
$D_{i,t}^{\text{Impacted}}$	0.018	-0.007
	(1.453)	(-1.285)
$D_{i,t-1}^{\text{High Exposure}}$	0.005	-0.001
	(1.092)	(-0.346)
$D_{i,t}^{\text{Impacted}} \times D_{i,t-1}^{\text{High Exposure}}$	-0.001	0.003
	(-0.205)	(0.991)
$\log(\text{TA})_{i,t}$	-0.003	-0.012**
	(-1.518)	(-2.890)
$B/M_{i,t}$	-0.007**	-0.001
	(-2.782)	(-0.307)
$ROA_{i,t}$	0.022**	0.026***
	(2.765)	(4.036)
$CapEx_{i,t}$	-0.012	0.023
	(-0.481)	(0.576)
Obs.	11,491	11,525
R^2 Adj.	0.051	0.044
Firm FE	YES	YES

Table A.3.10: Stock market reactions to first-time and recurrent natural disasters in the UK. This table reports the results of estimating equation (3.2) separately for firms located in areas experiencing natural disaster exposure for the first time during the sample period and for those located in areas affected by recurrent natural disasters. In all columns, the dependent variable is the cumulative market-adjusted return for treatment and control firms over the $[-5, +5]$ period. Column (1) presents results for firms exposed to a natural disaster for the first time, while Column (2) reports results for firms located in areas hit by more than one natural disaster during the sample period. In columns (1) and (2), $D_{i,t-1}^{\text{High Exposure}}$ takes the value of one if the firm physical climate-text average is greater than the sample physical climate-text average the year before a natural disaster event. Firm-level control variables include Log (TA), B/M, ROA, and CapEx. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.3.1 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	$CAR_{i,t}[-5, +5]$	
Sample of affected firms:	First-time exposure	Recurrent exposure
Specification:	(1)	(2)
$D_{i,t}^{\text{Impacted}}$	-0.031***	-0.017**
	(-5.067)	(-2.289)
$D_{i,t-1}^{\text{High Exposure}}$	0.002	0.007
	(-0.194)	(1.419)
$D_{i,t}^{\text{Impacted}} \times D_{i,t-1}^{\text{High Exposure}}$	0.015**	0.005
	(2.019)	(1.610)
$\log(\text{TA})_{i,t}$	-0.010**	-0.003
	(-2.530)	(-0.673)
$B/M_{i,t}$	-0.011***	-0.009**
	(-2.642)	(-2.314)
$ROA_{i,t}$	0.039***	0.029*
	(3.081)	(1.957)
$CapEx_{i,t}$	-0.082*	-0.081*
	(-1.842)	(-1.738)
Obs.	7,466	6,999
R^2 Adj.	0.108	0.035
Firm FE	YES	YES

Chapter 4

Climate Adaptation Disclosure: Does it Bring Home the Green?

4.1 Introduction

As explained in Chapter 2, a growing body of work in climate finance analyses the effects of climate risk disclosure on firm value. Researchers have started exploring how stock investors price the disclosure of companies' exposure to physical climate risks posed by a warming planet (Nagar and Schoenfeld, 2024) and to climate transition risks associated with a shift towards a low-carbon economy (Sautner et al., 2023a). However, no empirical study has systematically examined how investors price firms' strategies to *adapt* to physical climate risks. We fill this gap by examining the implications of climate adaptation disclosures on the stock price of UK companies listed on the London Stock Exchange. Historically, UK firms have been granted a high level of discretion for reporting their responses to physical climate risks. This provides an ideal setting for assessing how investors value these voluntary climate-related information releases.

Climate adaptation disclosure, with its potential to mitigate investors' uncertainty, is expected to enhance the liquidity of a company's securities when extreme weather events materialise (Diamond and Verrecchia, 1991). This, in turn, can help safeguard firm value (Easley and O'hara, 2004). However, theoretical models that also consider the *costs* of disclosure provide conflicting predictions on how voluntary disclosure can influence firm value (Goldstein and Yang, 2019). Two specific channels are particularly relevant when considering the costs of climate adaptation disclosure. First, management may face uncertainty regarding how investors perceive this kind of information, leading firms to consider partial or low disclosure as a safer option (Bond and Zeng, 2022). Second, investors may not learn from corporate signals about climate adaptation because considered as mere "cheap talk" that conceal questionable commitment to sustainable-related initiatives (Farrell, 1995). In this paper, we consider how climate adaptation disclosure may impact firm value by drawing from information disclosure theories and asset pricing theories. The former provide predictions about how corporate disclosure can influence investors' uncertainty and, as a result, firm value. The latter offer a rigorous framework to test these predictions empirically.

We make two main contributions. First, we show, for the first time, how investors price climate adaptation disclosure at the firm level. Our evidence suggests that by limiting their analysis to disclosing and not disclosing firms, previous research on climate finance has overlooked the importance of different types of disclosure, and their effects on firm value. Specifically, we first distinguish between physical climate risk disclosure and climate adaptation disclosure by employing textual analysis of UK firms' annual reports with two distinct climate-related dictionaries. The first dictionary, introduced in Chapter 3, enables us to separate firms disclosing material exposure to physical climate risks from firms making either no or low disclosure of such risks (Nagar and Schoenfeld, 2024). With the second dictionary we detect, among firms disclosing physical climate risks, those that employ specific climate adaptation *verbs* when describing their climate adaptation strategies.[1] We then analyse how stock investors price disclosure of climate physical risk exposure and climate adaptation at the firm level, using natural disasters as exogenous shocks to the investors' uncertainty about the information quality of companies' fundamentals (also defined as information uncertainty (Epstein and Schneider, 2008)). We find that, when analysing cumulative abnormal stock returns around natural disaster events, companies that disclose physical climate risks benefit from a lower stock price decline than firms that also disclose climate adaptation measures. These lower losses range from 1.7% to 1.4%, compared with an average loss of 2.3% for disaster-affected firms that either do not disclose physical climate risks, or that do so but also make climate adaptation disclosures. Our results are confirmed by several robustness checks including placebo tests and a validation of our climate adaptation dictionary based on the most advanced large language model to date, Open AI's GPT-4.

Our second contribution is to show the specific mechanisms under which climate adaptation disclosure may influence firm value in times of high information uncertainty. Building on the asset pricing framework proposed in Chapter 3, we find that investors favour firms that make physical climate risk disclosure but not climate adaptation disclosure because only the former mitigates information uncertainty around natural disasters. We prove this by analysing stock liquidity around these events as a proxy for information uncertainty and find that indeed stock liquidity is higher only for firms that do not disclose climate adaptation measures. Further tests corroborate the idea that the heterogenous pricing between physical climate risk disclos-

[1]Although Li et al. (2024) employed this approach to measure firm proactiveness in managing climate *transition* risks, our study reveals that this methodology can also be used to capture firms' adaptation to *physical* climate risks. For instance, we show that the dictionary of climate adaptation verbs allows us to identify companies in the Energy or Basic Resource sectors *investing* in tangible assets to deal with flood exposure. We provide further examples in Table A.4.4.

ure and climate adaptation disclosure is driven by their asymmetric effects in mitigating investors' ambiguity, as we detect no significant cash flow or stock volatility changes amongst firms that make climate adaptation disclosures. These findings allow us to reject the cash-flow (Nagar and Schoenfeld, 2024) and risk-based (Liu et al., 2017) explanations of stock price reactions to natural disaster events among firms disclosing their climate adaptation measures. Overall, our results are consistent with the idea that, historically, UK firms may have concealed disclosure of climate adaptation efforts to avoid the "cost" of investors' misjudging this information. A recent interview with managers of FTSE100 and FTSE All-Share firms, which are part of our sample, provides strong anecdotal evidence consistent with this notion (Tang, 2022). Specifically, one point that emerged from the Tang (2022) interviews is that "c*ommunicating this information clearly and in positive terms can be difficult, and the potential for stakeholders to misinterpret information about climate risks and responses to them is considerable*".

We have also examined the hypothesis that investors perceive climate adaptation disclosure as a form of cheap-talk (Bingler et al., 2024). To test this, we collected data from the Violation Tracker UK, which provides information about enforcement (including climate-related) actions brought against UK firms. We do not find any evidence indicating that companies disclosing about climate adaptation are more likely to have low levels of sustainable-related compliance, thus contradicting the cheap-talk explanation.

Our study has relevant implications for policies aimed at mandating the disclosure of climate-related information in companies' annual reports. First, a mandatory framework for physical climate risk disclosure may achieve the desired policy effects of reducing investors' uncertainty following a natural disaster event, thereby mitigating the negative impacts on stock liquidity and firm value. Additionally, our findings suggest that recent regulations, aligned with the *standardised* framework recommended by the Task Force on Climate-related Financial Disclosures (TCFD) for reporting on climate risk management at the firm level, can have a justifiable role in mitigating the perceived ambiguity associated with climate adaptation disclosure.

The remainder of the paper is organised as follows. Section 4.2 describes the regulatory environment for climate adaptation disclosure in the UK. Section 4.3 presents our hypotheses. Section 4.4 describes the data. Section 4.5 presents the construction, properties, and validation tests of the physical climate risk and climate adaptation measures. Section 4.6 discusses our model specification. Section 4.7 presents the results and the underlying mechanisms of the study. Finally, Section 4.8 provides concluding remarks.

4.2 Background: Climate Adaptation Disclosure in UK and U.S. Annual Reports

The regulation of climate adaptation disclosure in the United Kingdom has evolved as a complementary dimension to the country's broader climate governance framework. Whereas earlier initiatives primarily targeted the mitigation of greenhouse gas emissions, adaptation regulation has sought to ensure that firms identify and manage the physical risks posed by climate change. This focus on adaptation reflects the UK Government's statutory commitments under the *Climate Change Act 2008*, which introduced both legally binding emission reduction targets and the *Adaptation Reporting Power* (ARP). The ARP enables the Secretary of State to invite organisations in critical sectors (such as energy, transport, and water) to report on their exposure to and preparedness for climate risks within designated reporting cycles (known as ARP rounds). These reports feed into the National Adaptation Programme, aiming to enhance systemic resilience to climate change.

Despite the ARP's significance as a policy instrument, it has historically relied on a cooperative and selective approach rather than universal mandates. Firms not formally invited to participate remain under no statutory obligation to disclose adaptation-related information in their annual reports. This voluntary dimension contrasts sharply with the UK's more comprehensive and mandatory carbon reporting framework introduced through the *Companies Act 2006 (Strategic and Directors' Reports) Regulations 2013*. Even following the Financial Conduct Authority's (FCA) 2020 adoption of disclosure standards aligned with the *Task Force on Climate-related Financial Disclosures* (TCFD), adaptation information remains governed by a flexible "comply or explain" principle rather than prescriptive metrics or uniform disclosure templates.[2] Consequently, institutional investors have reported continued difficulty in assessing how companies intend to adapt to material climate risks (FRC, 2020).

By contrast, the United States presents a markedly different regulatory trajectory for climate adaptation disclosure. Whereas the UK has progressively centralised its disclosure regime under the supervision of the FCA and Department for Environment, Food and Rural Affairs (DEFRA), the U.S. framework remains fragmented across jurisdictions and legal domains. The Securities and Exchange Commission (SEC) adopted a federal climate disclosure rule in March 2024, which, while encompassing physical risk disclosure, has been stayed pending judicial review. In the absence of an enforceable federal standard, state-level initiatives have emerged as the primary drivers of climate-related transparency. These statutes do not explicitly target adaptation planning but implicitly require firms to assess their resilience to physical climate hazards in order to meet risk disclosure obligations. This decentralised U.S. approach produces significant heterogeneity in disclosure scope and timing, reflecting the broader political and legal contestation surrounding climate policy at the federal level. Firms operating across multiple

[2] For more information, see: `https://www.fca.org.uk/firms/climate-change-sustainable-finance`.

states must navigate overlapping or conflicting requirements, while ongoing litigation over regulatory authority introduces further uncertainty. Nevertheless, this system of overlapping mandates and investor-driven initiatives has spurred a diverse set of voluntary adaptation disclosures in sustainability reports and SEC filings, often influenced by private standard-setters such as the Sustainability Accounting Standards Board (SASB) and the TCFD.[3]

Overall, the UK's adaptation disclosure regime exemplifies a top-down, government-coordinated model grounded in statutory authority and guided implementation cycles, albeit with limited mandatory scope. The U.S. model, by contrast, is bottom-up, litigation-sensitive, and shaped by subnational experimentation and market pressure. Whereas UK firms operate within a predictable institutional environment characterised by gradual convergence toward the forthcoming ISSB-aligned *UK Sustainability Disclosure Standards*, U.S. firms face a patchwork of evolving obligations whose boundaries will ultimately depend on judicial outcomes and state policy trajectories.

This divergence in regulatory design has important implications for both investors and policymakers: the UK's structured yet selective adaptation reporting fosters comparability but risks underrepresenting firm-level exposure outside invited sectors, while the U.S. framework encourages innovation in voluntary reporting but lacks consistency and enforceability. Against this contrasting backdrop, the present study investigates how investors in the UK capital market respond to corporate disclosures relating specifically to climate adaptation, an area where regulatory signals remain relatively weak despite growing financial relevance.

[3]For more information, see: `https://impact.wharton.upenn.edu/wp-content/uploads/2021/04/Climate-Disclosures-Primer.pdf`

4.3 Hypothesis Development

Asset-pricing models of information uncertainty predict that, in equilibrium, information uncertainty commands an ambiguity premium (Epstein and Schneider, 2008). In our context, information uncertainty relates to investors' uncertainty caused by past and new information that is relevant for estimating firm value. In this chapter, we focus on the information uncertainty caused by natural disaster events, which allow us to focus on both sources. Specifically, natural disasters represent exogenous shocks increasing not only uncertainty about the *future* information quality of firm fundamentals, but also force investors to re-interpret the meaning and implications of *past* corporate disclosures about physical climate risks.

The goal of this chapter is to understand whether, across firms that report physical climate risks, those that also disclose climate adaptation can help investors mitigate the uncertainty effects caused by natural disasters. Intuitively, by signalling corporate preparedness to physical climate risks, the *benefits* of climate adaptation disclosure for a firm should manifest in the form of attenuated uncertainty for investors when the effects of climate change materialise. In turn, this mitigated investors' uncertainty should alleviate adverse impacts on stock liquidity and firm value (Diamond and Verrecchia, 1991; Guay and Verrecchia, 2018). This mechanism linking investors' uncertainty, the extent of disclosure and firm value represents the general prediction of theoretical models of information disclosure where "more information is always better than less information" (Easley and O'hara, 2004).

However, the beneficial effects of disclosure become more nuanced once the behavioural and strategic dimensions of information transmission are considered. From a behavioural-finance perspective, investors' biases may represent an important cost to consider for managers as they impact how information about climate adaptation is perceived and processed. In particular, disclosure of climate adaptation measures can unintentionally increase attention to company's physical risk exposure through salience and availability effects (Tversky and Kahneman, 1973), as well as through ambiguity aversion, as investors may discount information that increases interpretive uncertainty (Epstein and Schneider, 2008). Moreover, because climate adaptation information is usually conveyed through qualitative, narrative-based reporting, investor responses are shaped not only by informational content but also by its tone and framing (Hirshleifer and Teoh, 2003; Shiller, 2020). References to "climate threats" or "vulnerability" are other reasons that may increase perceived risk salience rather than signal company preparedness. Thus, even credible disclosures might not mitigate investor uncertainty around natural disaster events if the narrative frame around climate adaptation activates loss-focused rather than opportunity-focused cognition.

Another cost of releasing such information is that investors might suspect climate adaptation claims to be unverifiable or motivated by legitimacy concerns (Farrell, 1995). In that case, disclosure loses credibility and fails to reduce information asymmetry. From this perspective, climate adaptation information may not be informative because it sits in the grey zone between genuine strategic preparedness and symbolic compliance. The resulting scepticism would therefore be consistent with the behavioural biases that drive ambiguity premia in markets given cheap talk in ESG information and corporate greenwashing behaviour (Bingler et al., 2024).

From a strategic-disclosure perspective, managers may anticipate these investor heuristics and adjust their communication accordingly. In line with this, Tang (2022) find that many UK managers refrain from, or selectively disclose, climate adaptation information because they expect investors to misinterpret it or doubt its credibility. In this context, the disclosure decision is endogenous and strategic: managers balance reputational gains from transparency against the risk that climate adaptation narratives will be perceived as "cheap talk" or as exposing potential unpreparedness. Consequently, climate adaptation reporting can signal both responsibility and vulnerability, leading managers to prefer “silence” as a safer option (Bond and Zeng, 2022).

Thus, despite potential transparency benefits, behavioural biases, credibility concerns, and strategic disclosure choices may collectively explain why climate adaptation disclosures often fail to reduce investors' uncertainty around natural disaster events. Therefore, we formulate the following two hypotheses regarding the effects of information uncertainty and climate adaptation disclosure on firm value:

Hypothesis 1A: *Natural disaster events create information uncertainty at the firm level, leading to negative returns for disaster-affected firms.*

Hypothesis 1B: *Among firms that disclose physical climate risks, climate adaptation disclosure does not mitigate the negative effects of information uncertainty on stock returns when a company is impacted by a natural disaster.*

The theory of asset pricing provides a rigorous framework for analysing the channels that could justify the negative stock returns around natural disaster events: a decline in future cash flows (Nagar and Schoenfeld, 2024), which we call the “cash flow channel”, and an increase in the premium required by investors because of information uncertainty (Epstein and Schneider, 2008), which we denote as the “discount rate channel”. Regarding the first channel, a company's climate adaptation disclosure could lead investors to expect a contraction in future cash flows if they question the effectiveness of the company's adaptation strategies. We state the cash flow channel hypothesis as follows:

Hypothesis 2A (Cash flow hypothesis): *Expected cash flows decrease after a natural disaster, both for impacted firms and for those impacted firms disclosing climate adaptation.*

We investigate the discount-rate channel by analysing the change in stock liquidity over natural-disaster events. According to asset-pricing and behavioural theory, ambiguity-averse investors reduce market participation when they anticipate an increase in information uncertainty (Rehse et al., 2019). A decrease in stock liquidity following a natural disaster would therefore be consistent with investors seeking higher ambiguity premia (Epstein and Schneider, 2008). Furthermore, disclosures that are complex, qualitative, or perceived as self-serving may fail to mitigate perceived ambiguity around natural-disaster events. As Tang (2022) documents, firms may communicate climate adaptation efforts cautiously or inconsistently due to reputational concerns, leading investors to interpret such signals as strategic impression management rather than credible commitment. Under this framing, climate-adaptation disclosure does not attenuate investor uncertainty. We therefore hypothesise that:

Hypothesis 2B (Climate uncertainty hypothesis): S*tock illiquidity increases after natural disasters, both for impacted firms and for those impacted firms disclosing climate adaptation.*

4.4 Data and Descriptive Statistics

Given that the research question addressed in this chapter constitutes an extension of the analysis undertaken in Chapter 3, we employ a similar dataset as previously described. In this section, we describe how we employed specific data sources, taking into account the results in Chapter 3. Table 4.1 reports summary statistics for the primary variables used in this chapter, while Table A.4.1 provides their definitions.

Regarding the textual data, we continue to use corporate annual reports (in PDF format) for all UK-listed firms on the London Stock Exchange (LSE) with fiscal year-ends between January 1996 and December 2018. Employing annual reports to measure firm-level climate adaptation offers two key advantages. First, all LSE-listed firms are legally required to submit an annual corporate report, which helps mitigate potential selection bias that could arise from relying on voluntary disclosure channels (such as earnings conference calls or disclosures to the Carbon Disclosure Project (CDP)).[4] Second, unlike the CDP's standardised survey format, UK corporate reporting remains unstandardised, granting management substantial discretion over the structuring and presentation of disclosed information (El-Haj et al., 2020). This flexibility is particularly valuable for capturing cross-sectional heterogeneity in climate adaptation strategies across and within sectors, which might otherwise be less evident under more rigid reporting formats.

For the financial data, we again merge the annual report dataset with accounting information in British pounds (GBP) sourced from Worldscope, Financial Analysis Made Easy (FAME), and Compustat Global. As in the previous chapter, we exclude all firms classified as "Financials" according to the Industry Classification Benchmark (ICB) system. This exclusion allows us to focus on non-financial firms, which are more likely to act as end-users of hedging instruments against physical climate risks. Financial firms, in contrast, may mention such instruments in their disclosures primarily in their role as providers rather than users. We also collect data on stock returns and liquidity from Thomson Reuters DataStream, and follow the data-cleaning proposals suggested by Landis and Skouras (2021). Additionally, we obtain analyst earnings forecasts from the Institutional Brokers' Estimate System (IBES), which we employ to disentangle the cash flow and discount rate channels in our asset pricing analysis. Table 4.1, Panel B, presents summary statistics for the key financial variables, with corresponding definitions again provided in Table A.4.1.

Finally, building on the firm-level disclosure and asset pricing results regarding natural disaster exposure in Chapter 3, our analysis focuses ex-

[4]While we include all UK-listed firms to address concerns around selection bias, another important source of potential bias relates to the type of information firms elect to disclose. As discussed in Section 4.2, firms retain discretion over how they communicate their climate adaptation strategies to investors. In our robustness checks, we conduct additional analyses to address potential endogeneity concerns arising from this form of self-selection.

clusively on natural disaster exposure at the headquarters level. For this purpose, we use FAME as the primary source of firm location data, capturing firm headquarters' locations at the city or town level. We spatially merge these data with natural disaster records from the Geocoded Disasters (GDIS) dataset (Rosvold and Buhaug, 2021). Importantly, we restrict the sample to disasters recorded at the second administrative level within the UK (i.e., county-level exposure).

4.5 Climate Risk and Climate Adaptation Measures

4.5.1 Measurement

We measure firm-level physical climate risk disclosure and climate adaptation disclosure through the textual analysis of UK annual reports and two purpose-built dictionaries. The first dictionary containing physical climate risk terms was described in section 3.5.1 in Chapter 3.

To build the second dictionary containing terms related to climate adaptation we followed an approach similar to that described by Li et al. (2024), who analysed firm proactiveness in managing climate transition risks. Specifically, we identified climate adaptation strategies using *verbs* that denote a firm's willingness to manage its physical climate risk exposure. We constructed a dictionary of climate-adaptation verbs using the following steps. First, using part-of-speech tagging techniques, we analysed all verbs appearing in sentences containing terms in the physical climate risk dictionary across annual reports.[5] Then, we retained a list of 30 verbs to identify firms' responses

[5]The specification we use in our asset pricing tests considers only verbs appearing in the same sentence where climate risk terms appear, as we consider this procedure more reliable to avoid the possibility of false positives. In our robustness tests in Section 4.7.3, we evaluate the sensitivity of our findings to this specification and find very similar results

to physical climate risks.[6] To verify that our selected list of verbs can detect adaptation to physical climate risks at the firm level, we compared the classification performances of these verbs with those provided by advanced Large Language Models developed by OpenAI. The results of these exercises are summarised in Appendix 4.10.2.

Using these verbs, we constructed alternative measures to differentiate between firms that disclose both their climate adaptation strategies and exposure to physical climate risks and those that report only the latter. Specifically, our first proxy for corporate adaptation to physical climate risks is the *climate-adaptation ratio*, or $\mathrm{TM}_{i,t}^{\mathrm{Adaptation}}$, which is the ratio between the number of physical climate risk terms in the proximity of climate-adaptation verbs and the total number of physical climate risk terms in an annual report. We also constructed a *climate no-adaptation ratio,* or $\mathrm{TM}_{i,t}^{\mathrm{No\ Adaptation}}$, defined as the ratio between the number of physical climate risk terms not appearing in the proximity of climate-adaptation verbs and the total number of physical climate risk terms in an annual report. Summary statistics for both these measures are reported in Table 4.1, Panel A.

To simplify the econometric interpretation of our asset pricing tests, we use the $\mathrm{TM}_{i,t}^{\mathrm{Adaptation}}$ variable to define a firm as taking climate adaptation measures in a certain year using a dummy variable, $D_{i,t}^{\mathrm{Adaptation}}$, which is equal one when such measures are adopted. This dummy variable was constructed using two alternative specifications, indicating different degrees of climate adaptation at the firm level. Specifically, $D_{i,t}^{\mathrm{Adaptation}}$ can take the

when incorporating climate adaptation verbs appearing in the preceding or subsequent sentences containing physical climate risk terms.

[6]These verbs are: *accelerate, adapt, add, alleviate, approve, assess, bolster, boost, engage, ensure, formalise, handle, improve, install, invest, make, meet, modify, participate, predict, promote, provide, refine, rehabilitate, reinforce, replace, replenish, start, stimulate, update.* For each of these verbs, we considered its present simple (including third person singular), past tense and present participle forms. Importantly, given that the selection of these verbs relies on our judgment based on a careful review of a sample of UK annual reports, we test whether our results are sensitive to alternative climate adaptation verbs and the number of verbs (30, 40, or 50) used to construct the climate adaptation dictionary. In our robustness section, we demonstrate that the main results of the paper remain unchanged when considering alternative verb dictionaries.

value of one if, in a certain year, the *climate-adaptation ratio* for a generic firm is greater than zero ($D_{i,t}^{Adaptation(I)}$) or greater than 50% ($D_{i,t}^{Adaptation(II)}$). The first measure simply indicates the *presence* of any type of climate adaptation strategy at the firm level. The intuition behind this measure is that the mere presence of a single strategy against physical climate risks reported in corporate reports may be sufficient for investors to identify firms engaged in climate adaptation. On the other hand, the second measure, similar to $\text{TM}_{i,t}^{\text{Adaptation}}$, proxies for the *intensity* with which firms want to signal their climate adaptation strategies to investors.[7] Summary statistics for these variables are reported in Table 4.1, Panel A.

4.5.2 Descriptive Findings

In this section, we present preliminary evidence regarding the characteristics of our climate adaptation measures and relate them to the properties of the physical climate risk measure. We focus on the $\text{TM}_{i,t}^{\text{Adaptation}}$, $D_{i,t}^{Adaptation(I)}$ and $D_{i,t}^{Adaptation(II)}$ measures, given that the proxies of climate adaptation represent the main focus of our paper.

First, Table A.4.2 reports the most common physical climate risk keywords appearing in the proximity of climate adaptation verbs. Table A.4.2 shows two interesting findings. First, the term "*weather*" is the most frequent keyword discussed when UK firms disclose their climate adaptation strategies. Previous research found that this keyword can capture both acute (Nagar and Schoenfeld, 2024) and chronic (Li et al., 2024) climate risk exposure at the firm level, thus confirming that the climate adaptation measures are indicative of firms' readiness to address these types of risks. Second, flood exposure (as indicated by the keywords "flooding", "floods" and "flood damage") emerges as the predominant category of natural disaster for which UK firms are adapting. This finding is consistent with the anecdotal evidence

[7] In our robustness tests in Section 4.7.3, we use all three specifications to demonstrate the validity of our findings.

found in Tang (2022), who shows that this type of physical climate risk represents one of the main concerns of UK managers when dealing with climate adaptation planning.

Subsequently, we examine industry-specific patterns. Table A.4.3 reports the mean values ranked by industry for the physical climate risk measure, as well as the climate adaptation measures. The comparison of the four panels in Table A.4.3 shows the presence of several relevant patterns. First, consistent with previous findings in the literature (Li et al., 2024; Sautner et al., 2023a), companies operating in sectors related to Utility, Food, Beverage, and Tobacco, as well as Basic Resources and Energy exhibit high levels of physical climate risk exposure (Panel A). As noted in Li et al. (2024), firms operating in these sectors have significant exposure to disruptions caused by physical climate risks, given that a substantial portion of their corporate activities occurs outdoors. Second, we observe some interesting differences in the rankings provided by the mean values of climate adaptation measures across industries. For instance, Utilities always rank high for the mean values of $\text{TM}_{i,t}^{\text{Adaptation}}$ (Panel B), $D_{i,t}^{Adaptation(I)}$ (Panel C) and $D_{i,t}^{Adaptation(II)}$ (Panel D). This pattern is consistent with Goldstein et al. (2019), who find that firms in this sector are important catalysts in experimenting various types of climate adaptation strategies. On the other hand, Food, Beverage, and Tobacco rank high only for $D_{i,t}^{Adaptation(I)}$, and not for $\text{TM}_{i,t}^{\text{Adaptation}}$ and $D_{i,t}^{Adaptation(II)}$ (Panels B and D). This suggest that firms in this sector prefer to provide signals about the presence, rather than intensity, of their climate adaptation strategies. However, even if the variation in climate adaptation strategies that we detect across industries may be explained by industry-inherent factors (Goldstein et al., 2019), the third relevant pattern to note in Table A.4.3 is that the heterogeneity persists also *within* each industry. This observation becomes evident when examining the high standard deviation in the climate adaptation measures for each industry. To provide further evidence of this point, we conduct a comparative analysis of Anglo

American and BHP, two companies within the Basic Resource sector, both of which are constituents of the FTSE100 index. Both companies have a similar average value for the $\text{TM}_{i,t}^{\text{High Exposure}}$ variable (0.198 for Anglo American against the 0.175 of BHP). However, these firms rank differently in terms of the mean values of $\text{TM}_{i,t}^{\text{Adaptation}}$ (0.205 for Anglo American against the 0.071 of BHP). Intriguingly, the advanced level of climate adaptation strategies exhibited by Anglo American in comparison to other companies operating within the Basic Resources sector was also acknowledged in a recent report by Crawford and Seidel (2013). Their analysis delved into the responses of S&P100 companies to physical climate risks, a group to which both Anglo American and BHP belonged at the time of the study. This evidence underscores the value of annual reports as a valuable textual source for accurately capturing climate adaptation strategies across and within industries.

Finally, Table A.4.4 reports the excerpts of the annual reports of the firms with the highest values of $\text{TM}_{i,t}^{\text{Adaptation}}$ (and for which both $D_{i,t}^{Adaptation(I)}$ and $D_{i,t}^{Adaptation(II)}$ equals one). Consistent with the information in Table A.4.3, Table A.4.4 provides anecdotal evidence that several companies in different sectors are exposed to threats from physical climate risks. In response, firms have implemented a series of climate adaptation strategies to manage this exposure. For instance, Aurelian Oil & Gas PLC, an Energy sector company, disclosed its approach to managing flood exposure by *investing* in tangible assets to protect its facilities from this particular kind of physical climate risk. Furthermore, Albert Fisher Group PLC, a company operating in the Food, Beverage and Tobacco sector, emphasized the importance of geographically relocating its suppliers to *ensure* the resilience of its supply chain against frost-related crop damage.[8] The aim of this paper is to understand how this information influences investors' uncertainty when the risks it is intended to address are material.

[8]Changes in climate can alter the timing of key stages of crop development, such as budbreak and flowering. This can increase the risk of exposure to adverse weather conditions, including frost. For more information, see: `https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0141218`

4.5.3 Validation of the Climate Adaptation and No-Adaptation Measures

In this section, we investigate whether the climate adaptation and no-adaptation measures capture differences in future real-business activities and sustainability performances across firms. To study this, we estimate the following model:

$$Z_{i,t+1} = \alpha + \beta_1 \mathrm{TM}_{i,t}^{\mathrm{Adaptation}} + \beta_2 \mathrm{TM}_{i,t}^{\mathrm{No\ Adaptation}} + \gamma \mathbf{X}_{i,t} + \theta_i + \vartheta_t + e_{i,t+1} \quad (4.1)$$

where $\mathrm{TM}_{i,t}^{\mathrm{Adaptation}}$ represents the climate adaptation ratio, while the variable $\mathrm{TM}_{i,t}^{\mathrm{No\ Adaptation}}$ represents the climate no-adaptation ratio.[9] The term $\mathbf{X_{i,t}}$ is the same vector of control variables used in eq. (3.1). We control for firm fixed effects (θ_i) and year fixed effects (ϑ_t) and clustered the standard errors conservatively at the firm and year levels (Petersen, 2008). We use different specifications of the $Z_{i,t+1}$ variable to study dynamics related to either future real-business activities or sustainability outcomes across firms.

In the first set of validation tests, we analyse how the two textual measures correlate with future capital expenditures (CapEx) and research and development (R&D) expenditures. Recent research in climate economics shows that responses to physical climate risks can take the form of investments to adapt fixed assets to changing climate conditions (Lin et al., 2020) and innovation in climate adaptation technologies (Miao and Popp, 2014; Touboul et al., 2023). Therefore, if our climate adaptation measure is proxying for investments in climate-resilient plans and innovation, we expect the coefficient β_1, and not β_2, to be positive and statistically significant. We

[9] We obtain qualitatively similar results for the tests in this section when we replace the $\mathrm{TM}_{i,t}^{\mathrm{Adaptation}}$ variable with either the $D_{i,t}^{Adaptation(I)}$ or $D_{i,t}^{Adaptation(II)}$ variables.

report the results of tests about capital and R&D expenditures in the first two columns of Table 4.2, respectively. The results in Column (1) indicate that only the coefficient β_1 in eq. (4.1) is positive and statistically significant (at the 5% level). This suggests that firms disclosing their climate adaptation strategies have higher levels of CAPEX than firms mainly disclosing about physical climate risks. Similarly, Column (2) shows a positive and statistically significant association between future R&D expenditures and the climate adaptation measure only. Overall, these results align with the notion that adaptation disclosures in corporate reports are related to higher investment and innovation within the company.

In our second set of validation tests, we investigate how the two textual measures correlate with Environmental, Social, and Governance (ESG) ratings and Environmental ratings, as well as environmental violations at the firm level. Although ESG and Environmental scores may not directly measure climate adaptation, they do capture how firms address sustainable and environmental issues, which may include solutions related to climate adaptation (Li, 2025). By contrast, climate adaptation disclosures may be used by corporations as a form of greenwashing to mislead investors (Bingler et al., 2024). In such a scenario, we would expect firms to voluntarily sponsor their climate adaptation initiatives to improve sustainability scores while downplaying sustainable-related compliance. We obtained firm-level data about overall Environmental, Social, and Governance (ESG) ratings, along with individual Environmental scores, from Refinitiv. To analyse the credibility of firms' commitments to sustainable-related issues, we retrieved data from the Violation Tracker UK database. This dataset covers enforcement actions against UK public and private companies by 49 government regulators.[10] Offences are classified as: (i) safety-related; (ii) environment-

[10]Importantly, Violation Tracker UK provides a unique ISIN identifier for sanctioned companies' parent firms. However, as companies may have multiple parents, we addressed this by merging the dynamic corporate structure dataset described in Section 3.4.3 with Violation Tracker UK data. The final merged dataset covers violations by 307 listed parent firms, expanding the initial 141 parents identified in Violation Tracker UK.

related; (iii) employment-related; (iv) financial; (v) competition-related; and (vi) consumer-protection-related. For our validation tests, we focus on environmental violations, which include climate-related violations.[11] Summary statistics for the firm-level proxies of sustainability performances are reported in Table 4.1, Panel D.

We report the results of the tests regarding ESG scores, Environmental scores, and environmental violations in the last three columns of Table 4.2, respectively. The results in Column (3) indicate that firms disclosing information about climate adaptation are more likely to achieve higher ESG scores than firms primarily reporting on physical climate risks. This result is significant at the 1% level. Column (4) further shows that only the climate adaptation measure correlates positively with future environmental scores, although this result is significant at the 10% level. Finally, we find no evidence that either the climate adaptation or the no-adaptation measure predicts the likelihood of a firm incurring future environmental violations.[12] Overall, the evidence from the second set of validation tests is important for two reasons. First, these results support the notion that the climate adaptation measure is related to ESG and environmental scores. However, our measure holds an advantage as it covers a longer period and is available for more companies than either type of sustainability score. In turn, this helps us to better infer how investors historically evaluated climate adaptation across firms and mitigate possible selection-bias concerns. Second, the findings regarding sustainable-related violations suggest that the disclosure of climate adaptation is not associated with greenwashing or "cheap talk" indicators by investors.

[11] For anecdotal evidence about this, see for instance: `https://violationtrackeruk.goodjobsfirst.org/violation-tracker/SSE-Hornsea-Limited`

[12] Additionally, we also estimated a probit regression employing the $D_{i,t+1}^{\text{Violation}}$ as dependent variable. Regression results under this specification (un-tabulated) corroborate the main outcomes about climate adaptation disclosure and environmental violations that we find when estimating eq. (3.1).

4.6 Model Specification

To investigate the firm value implications of company adaptation to physical climate risks, we employed an event study methodology. Similarly to the asset pricing analysis proposed in Chapter 3, we set as filter that the duration of a natural disaster did not exceed 30 days (Huynh and Xia, 2021).

The econometric framework employed in this chapter represents an extension of the approach proposed in eq. (3.2). In this chapter, to test whether climate adaptation disclosure influences the negative stock price reaction to a natural disaster for disaster affected firms (Hypothesis H1B), we split the $D_{i,t-1}^{\text{High Exposure}}$ dummy into two new dummies using a composite variable approach (Menzly and Ozbas, 2010): $D_{i,t-1}^{\text{Adaptation}}$ and $D_{i,t-1}^{\text{No Adaptation}}$. The $D_{i,t-1}^{\text{Adaptation}}$ dummy, which can assume two alternative specifications as described in Section 4.5.1, identifies high climate exposure firms that disclose climate adaptation measures the year before a natural disaster. The $D_{i,t-1}^{\text{No Adaptation}}$ dummy identifies high climate exposure firms that do not disclose climate adaptation the year before a natural disaster. Therefore, we extended eq. (3.2) as follows:

$$\begin{aligned}\text{CAR}_{i,t}[-5,+5] = \alpha &+ \beta_1 D_{i,t}^{\text{Impacted}} + \beta_2 D_{i,t-1}^{\text{No Adaptation}} + \beta_3 D_{i,t-1}^{\text{Adaptation}} \\ &+ \beta_4 D_{i,t-1}^{\text{No Adaptation}} \cdot D_{i,t}^{\text{Impacted}} + \beta_5 D_{i,t-1}^{\text{Adaptation}} \cdot D_{i,t}^{\text{Impacted}} \\ &+ \gamma \mathbf{X}_{i,t} + \theta_i + e_{i,t}\end{aligned} \tag{4.2}$$

By estimating eq. (4.2), we can isolate the effect of disclosing physical climate risks only (via $D_{i,t-1}^{\text{No Adaptation}}$), and the effect of disclosing physical climate risk as well as climate adaptation measures (via $D_{i,t-1}^{\text{Adaptation}}$), taking as reference group not impacted firms with low levels of physical climate risk disclosure.[13] If firm adaptation to climate change pays off when a natural disaster event occurs, we would expect the coefficient β_5 in eq. (4.2), and not β_4, to be positive and statistically significant. However, if only the climate risk disclosure dimension mitigates the effects of information uncertainty, we would expect β_4, and not β_5, to be positive and statistically significant.

4.7 Results

This section presents our main empirical findings. We start with an event study to examine how investors price climate adaptation and physical climate risk disclosure when a firm is impacted by a natural disaster. We then explore the possible channels behind these effects and test the validity of our baseline findings via a battery of robustness tests.

4.7.1 Event Study

As shown in Chapter 3, we find that investors react to natural disasters affecting the county in which the headquarters of UK firms are located (Hypothesis H1A). We also showed that the decline in stock price is less pronounced when the affected firm is transparent with investors about its exposure to physical climate risks.

In this chapter, we extend such analysis and investigate how investors

[13] The composite variable approach we employ to construct the $D_{i,t-1}^{\text{Adaptation}}$ and $D_{i,t-1}^{\text{No Adaptation}}$ variables has several advantages than other specifications, such as a triple difference-in-difference framework. First, it simplifies the model by reducing the number of interaction terms to consider, making it easier to interpret the effect of climate adaptation disclosure on firm value. Second, using composite variables helps reduce the dimensionality of the model, in turn increasing the statistical power of the analysis and mitigating possible multicollinearity concerns. However, in our robustness section, we considered the different climate adaption specifications defined in Section 4.5 (i.e., $\text{TM}_{i,t-1}^{\text{Adaptation}}$, $D_{i,t-1}^{Adaptation(I)}$ and $D_{i,t-1}^{Adaptation(II)}$) by expanding eq. (4.2) to estimate a triple-difference framework. As we show in that section, regression results under this additional specification corroborate the main outcomes about CARs that we find when estimating eq. (4.2).

price disclosure of climate adaptation during times of high information uncertainty (Hypothesis H1B). Figure 4.1 presents the unconditional cumulative abnormal returns of impacted firms with different types of climate-related disclosures from five trading days before to five days after a natural disaster event affecting ADL2 areas in the UK. Surprisingly, the graph shows that the CAR of affected firms disclosing climate adaptation exhibits a more similar pattern to that of affected firms with weak physical climate risk disclosure. On the other hand, affected firms that robustly and exclusively disclose physical climate risk show a far lower decrease in the CAR.

We next carry out regression analysis to check if the above unconditional evidence is confirmed. Table 4.3 reports the results. Consistent with the evidence in Figure 4.1, column (1) shows that affected firms that did not disclose climate adaptation strategies the year before a natural disaster event benefited from a highly statistically significant 170 basis point lower loss in value compared to affected but non-disclosing firms. This is evidenced by the value (0.017) of β_4, the coefficient of the interaction term $D_{i,t-1}^{\text{No Adaptation}} * D_{i,t}^{\text{Impacted}}$ in eq. (4.2). We do not observe a similar pattern for firms affected by natural disasters that disclosed climate adaptation strategies. Specifically, column (1) indicates that the value of β_5, the coefficient of the interaction term $D_{i,t-1}^{\text{Adaptation}} * D_{i,t}^{\text{Impacted}}$ in eq. (4.2), is approximately zero and statistically insignificant (t-value = 0.447). Column (2) shows similar estimates of eq. (4.2) for β_4 and β_5 when we consider the second climate adaptation specification defined in Section 4.6. To summarise, the results in Table 4.3 indicate that when climate change effects materialise, impacted firms that are transparent about their physical climate risk exposure are penalised less by investors. On the other hand, firms affected by these events that are also transparent about their efforts to adapt to these risks do not reap the same benefits.

4.7.2 Channels

This section aims to understand the underlying channels driving the results observed in the previous section, regarding the firm value implications of exposure to natural disasters and the relative effects of climate adaptation and no-adaptation disclosure. As explained in Chapter 3, a negative change in equity returns can be due to lower expected cash flows, higher uncertainty (discounting), or both (Liu et al., 2017). In the following subsections, we use the same framework proposed in Chapter 3 to analyse each of these possibilities in detail.

Cash Flow Channel

One possible explanation for the decline in equity returns around natural disasters for affected firms with weak physical climate risk disclosure and firms with both strong physical risk disclosure and climate adaptation disclosure is a decrease in their expected cash flows (Hypothesis 2A). To analyse this possibility, we rely on changes in analysts' earnings forecasts before and after natural disaster realisations as in Chapter 3. Table 4.4 presents the results in the first two columns. Overall, we find no significant evidence that analysts revise their EPS estimates downward for firms affected by natural disasters, regardless of their climate disclosure strategy.

We apply two further tests to investigate the robustness of these findings as in Chapter 3. First, apart from changes in expected cash flows, we employ *realised* cash flows as a proxy for changes in investors' expectations. Second, we analysed the short-selling activity of institutional investors around natural disaster events. We measured the changes in *realised* cash flows by considering the change in ROA from the year before to after a natural disaster event (ΔROA_i). With respect to short-selling activity, we constructed a dummy variable, D_i^{Short}, which equals one when a company was subject to short-selling by an institutional investor within the [-5, +5] period around a natural disaster event. Table A.4.5 presents the results. Consistent with the findings in the first two columns of Table 4.4, the results in Table A.4.5 do not provide evidence of lower realised cash flows or heightened short-selling activities when firms are affected by natural disasters and disclose climate adaptation strategies. In summary, the findings in the first two columns in Table 4.4 and in Table A.4.5 tend to reject Hypothesis 2A (the cash flow channel hypothesis).

Stock Return Volatility Channel

Another plausible explanation for our findings in Table 4.3 may be that natural disasters cause an increase in information uncertainty at the firm level. As in Chapter 3, we investigate the discount rate channel by considering two forms of investor uncertainty that could influence the premium dictated by information uncertainty, namely risk and ambiguity (Rehse et al., 2019). Risk is typically measured with stock return volatility (Liu et al., 2017; Rehse et al., 2019), while ambiguity is proxied with stock liquidity (Rehse et al., 2019). Therefore, in our empirical tests, we analyse both forms of investor uncertainty to discern better the relative impact of risk and ambiguity and ascertain which one contributes more significantly to driving the ambiguity premium around natural disaster events.

To examine changes in stock volatility, we adopt the approach outlined by Liu et al. (2017). Specifically, we computed a measure of abnormal volatility by calculating the percentage change in stock volatility from before to after a disaster event (ΔVol_i). Daily stock returns are used to construct volatility over a one-month post-disaster period. To account for seasonality, the pre-natural disaster period was defined as the same calendar time window as the preceding year (Liu et al., 2017).[14] To test Hypothesis 2B, we estim-

[14]Differently from Liu et al. (2017), we employed one year, as opposed to two years, to establish the benchmark period, thereby preserving a greater number of observations for

ated specifications similar to those in eq. (4.2) but replaced market-adjusted returns with the ΔVol_i variable.

Table 4.4 presents the results in the last two columns. The results suggest no substantial change in risk for firms affected by a natural disaster with low levels of climate risk disclosure and those that disclose climate adaptation strategies. Consequently, these outcomes tend to reject the possibility that our results are driven by increased risk aversion around natural disaster events.

Stock Liquidity Channel

Next, we assess whether the lower cumulative abnormal returns of firms disclosing about climate adaptation compared to those disclosing only physical climate risks might be attributed to lower stock liquidity in the aftermath of a natural disaster event (Hypothesis 2B). Consistent with Rehse et al. (2019), we employed two measures of stock liquidity: daily trading volume in British pounds and bid-ask spreads. Moreover, as in Rehse et al. (2019), we computed daily bid-ask spreads following the approach proposed by Chung and Zhang (2014). To disentangle the impact of ambiguity from the risk-based explanation, we constructed measures of abnormal volume and spreads similar to the abnormal volatility measures described in Section 4.7.2. Finally, we included abnormal volatility as a control when examining the relationship between natural disasters and stock liquidity. This approach enabled us to account for additional potential sources of confounding variation between stock liquidity and investors' ambiguity (Rehse et al., 2019).

Table 4.5 reports the results. The first two columns reveal a highly statistically significant increase of 0.185% in daily closing spreads following a natural disaster event, both for firms impacted by a natural disaster with

our analyses. Nonetheless, we also conducted tests using a reference period of two years, and this did not qualitatively change the conclusions of our findings.

low levels of physical climate risk disclosure and for those disclosing climate adaptation strategies. Notably, the first two columns of Table 4.5 also indicate that firms that only disclose physical climate risks benefit from a *smaller* increase in closing spreads. Specifically, the coefficients for the first and second climate adaptation specifications reported in the Table are -0.092 (t-value = -2.404) and -0.076 (t-value = -2.033), respectively. Furthermore, the last two columns show a 1.076% decrease in trading volume for firms impacted by a natural disaster with low levels of climate risk disclosure and for those disclosing climate adaptation strategies. These results are significant at the 1% level. Finally, in the last two columns in Table 4.5, we observe that natural disaster-affected firms that only disclose physical climate risks benefit from a smaller decrease in trading volume. These results are significant at the 1% level.

In summary, the findings in Table 4.5 support the notion that the negative impact on the CAR of affected firms following a natural disaster is driven by heightened investors' ambiguity caused by natural disasters. These results also indicate that while firm transparency about physical climate risks exposure can alleviate this ambiguity during times of high information uncertainty, the same does not apply to disclosure of climate adaptation.

Finally, the combined evidence from the empirical tests regarding the discount rate and cash flow channels provide further insights into our results. Specifically, the finding that natural disasters do not appear to cause a subsequent drop in corporate cash flows provides, if anything, a complementary rather than an alternative mechanism for why investors may struggle to perceive the value of climate adaptation disclosure. In particular, one of the primary reasons driving corporate expenses in climate adaptation measures is to enhance the resilience of cash flows against the impacts of natural disasters, especially over the long term (Crawford and Seidel, 2013). However, if historical data indicate no significant impact of natural disasters on cash flows, investors may face difficulty in understanding the necessity for the costs incurred when employing these types of corporate strategies.

Further Cross-Sectional Evidence: Industry Competition

Finally, we carry out cross-sectional tests across two subsamples: firms operating in competitive industries and not competitive industries. We measure the level of market competition in each industry by calculating the Herfindahl-Hirschman Index (HHI) annually. Lower (higher) HHI scores indicate less (more) industry concentration and, consequently, higher (lower) market competition. Accordingly, a firm is considered to operate in a competitive environment in a given year if its industry's HHI falls below the median value of the HHI distribution calculated for that year (Ilhan et al., 2023a).

On the one hand, Ilhan et al. (2023a) explained that firm transparency about climate *risk* exposure could be "costly" in competitive industries, as this disclosure may reveal proprietary information to company's rivals.[15] On the other hand, Verrecchia (1983) argues that managers will disclose proprietary information when the increase in firm value resulting from disclosure outweighs the proprietary costs. In our context, if the benefits of corporate transparency about climate risk exposure occur in terms of reduced investors' uncertainty, we expect the effects of these benefits to be particularly evident in market environments where such transparency may be costly, yet value relevant for investors.

Although the arguments in Ilhan et al. (2023a) and Verrecchia (1983) provide testable hypotheses on how transparency about climate risk disclosure may influence firm value in competitive industries, there is no clear theoretical guidance for making similar predictions about disclosure of climate adaptation. One could argue that firm expenditures aimed at enhancing

[15]Examples of this proprietary information could include details about specific corporate operations impacted by natural disasters, as illustrated in Table A.4.4.

corporate resilience to physical climate risks could confer a relevant competitive advantage, especially in competitive industries. However, anecdotal evidence from interviews conducted by Tang (2022) suggests that the potential loss of competitive advantage is among the reasons why managers may not find beneficial to disclose proprietary information regarding climate adaptation. As Tang (2022) explains: "*Adaptation reporting involves identifying and disclosing a company's weaknesses both to potential competitors and to other stakeholders whose responses to that information may significantly affect business performance*". Overall, whether firm transparency about climate adaptation mitigates investors' uncertainty in competitive industries is an empirical question.

Table 4.6 reports the results of eq. (4.2) when using either CAR, closing spreads or trading volume as dependent variables for the subsamples of companies operating in no-competitive industries and the subsamples of companies operating in competitive industries. For the subsample of firms operating in no-competitive industries, columns (1), (3) and (5) show that the coefficient on the term $D_{i,t}^{\text{Impacted}}$ is always statistically significant (at least at the 5% level), while the same does not hold true for the coefficients on the double interactions terms involving the climate adaptation and no-adaptation measures. In particular, only column (5) shows a slightly statistically significant coefficient (at the 10% level) on the double interaction term involving the no-adaptation variable. On the other hand, for the subsample of firms operating in competitive industries, columns (2), (4) and (6) show a highly statistically significant coefficient on the term $D_{i,t}^{\text{Impacted}}$, as well as a statistically significant coefficient only for the double interaction term $D_{i,t-1}^{\text{No Adaptation}} * D_{i,t}^{\text{Impacted}}$ in eq. (4.2). In un-tabulated analyses, we obtain similar results using the second climate adaptation specification when splitting the sample between companies operating in no-competitive industries and competitive industries. Overall, these findings suggest that the mild penalty in CAR documented in Table 4.6 is likely mainly driven by impacted firms disclosing physical climate risks in competitive industries.

4.7.3 Robustness Tests

In our first robustness test, we examine the validity of our findings to additional regression specifications. In particular, as an alternative to the composite variable approach employed in eq. (4.2), we estimated a triple difference-in-difference framework by extending eq. (3.2) as follows:

$$\begin{aligned} CAR_{i,t}[-5,+5] = {} & \alpha + \beta_1 D_{i,t}^{Impacted} + \beta_2 D_{i,t-1}^{High\ Exposure} + \beta_3 TM_{i,t-1}^{Adaptation} \\ & + \beta_4 D_{i,t}^{Impacted} \cdot D_{i,t-1}^{High\ Exposure} \\ & + \beta_5 D_{i,t}^{Impacted} \cdot TM_{i,t-1}^{Adaptation} \\ & + \beta_6 D_{i,t-1}^{High\ Exposure} \cdot TM_{i,t-1}^{Adaptation} \\ & + \beta_7 D_{i,t}^{Impacted} \cdot D_{i,t-1}^{High\ Exposure} \cdot TM_{i,t-1}^{Adaptation} \\ & + \gamma \mathbf{X}_{i,t} + \theta_i + \varepsilon_{i,t} \end{aligned} \tag{4.3}$$

To test the effect of climate adaptation disclosure on firm value during times of high information uncertainty (Hypothesis H1B), the main terms of interest in eq. (4.3) are represented by β_5 and β_7. The former captures the differential return impact for affected firms reporting about their climate adaptation strategies the year before a natural disaster event. The latter captures the differential return impact for affected firms with high levels of climate risk disclosure that also report about climate adaptation. To ensure completeness, we estimated eq. (4.3) by also considering the two additional climate adaptation specifications introduced in Section 4.5, namely $D_{i,t-1}^{Adaptation(I)}$ and $D_{i,t-1}^{Adaptation(II)}$. Also relevant is the coefficient β_4, which in this context isolates the effect on CAR of affected firms with high levels of climate risk disclosure that do not report about climate adaptation. Given that previous analyses show that only disclosure of physical climate risks decrease information uncertainty when a firm is impacted by a natural disaster, we expect only β_4, and not β_5 and β_7, to be positive and statistically significant. The results in Table A.4.6 confirm that it is indeed the case. Specifically, all three columns in Table A.4.6 show a positive and statistically significant coefficient on the double interaction term $D_{i,t}^{\text{Impacted}} * D_{i,t-1}^{\text{High Exposure}}$. On the other hand, the coefficients on the double interaction $D_{i,t}^{\text{Impacted}} * \text{TM}_{i,t-1}^{\text{Adaptation}}$ and the triple interaction term $D_{i,t}^{\text{Impacted}} * D_{i,t-1}^{\text{High Exposure}} * \text{TM}_{i,t-1}^{\text{Adaptation}}$ are statistically insignificant, regardless of the climate adaptation specification considered.

A second potential concern regarding our results is whether the fixed effect specification we have adopted in eq. (4.2) is appropriate for our staggered DID design (Baker et al., 2022). To address the validity of our setting, we applied two placebo tests, similar to those used byNagar and Schoenfeld (2024). These placebo tests involved assigning two false dates to each natural disaster event, one 30 calendar days prior to the actual date and the other 30 days after. Results are presented in Table A.4.7 which shows no statistically significant results for the placebo tests. Therefore, these tests mitigate the possibility that our main results on climate adaptation disclosure in Table 4.3 are driven by endogeneity concerns and confirm the robustness of our findings. In unreported results, we tested other potential sources of endogeneity more closely associated with self-selection bias, which could arise from strategic firm disclosure. Specifically, following Li et al. (2024), we excluded the top and bottom 10% of observations based on the physical climate risk ratio when estimating eq. (4.2) to alleviate the possibility that our findings are influenced by a subset of firms with an extreme tone regarding their climate risk or climate adaptation disclosures. Similar to the results shown in Table 4.3, our analysis indicates that only the coefficient on the double interaction term $D_{i,t}^{\text{Impacted}} * D_{i,t-1}^{\text{No Adaptation}}$ remains statistically significant (at the 1% level for both types of climate adaptation specifications) based on the restricted sample. These results suggest that the self-selection issue is not a major concern for our analysis.

The third potential concern is that our findings on climate adaptation disclosure may be driven by the specific climate-adaptation verbs chosen to identify firms' responses to physical climate risks. To address this, we applied two different types of validation tests. For the first test, we created 1,000 alternative specifications for the $\mathrm{TM}_{i,t}^{\mathrm{Adaptation}}$ measure to construct the $D_{i,t-1}^{\mathrm{Adaptation}}$ and $D_{i,t-1}^{\mathrm{No\ Adaptation}}$ variables in eq. (4.2), by considering two non-mutually exclusive options. Specifically, we constructed the $\mathrm{TM}_{i,t}^{\mathrm{Adaptation}}$ variable by randomly selecting 30, 40, or 50 climate adaptation verbs from a list of 190 verbs.[16] We then searched for climate adaptation verbs appearing in the: (i) same sentence; (ii) same and consecutive sentences; and (iii) previous, same and following sentences containing physical climate risk terms. Table A.4.8 presents the percentages of significant beta coefficients in eq. (4.2) over the 1,000 alternative specifications, across the two climate adaptation measure specifications described in Section 4.6. Consistent with the results in Table 4.3, the coefficient β_4 in eq. (4.2) was statistically significant (at 5% level) 97% of the time on average across the two specifications, while this percentage decreased, on average, to 7.5% for the β_5 coefficient.

For the second test, we constructed proxies for the variables $D_{i,t-1}^{\mathrm{Adaptation}}$ and $D_{i,t-1}^{\mathrm{No\ Adaptation}}$ in eq. (4.2) using text classifications from Open AI's GPT-4 and GPT-4o models, rather than those provided from of our list of climate adaptation verbs.[17] The results, based on the first definition of the climate adaptation variable, are reported in Table A.4.9 for both models.[18] Similar

[16]We select this list of 190 climate adaptation verbs applying the same procedure explained in Section 4.5.1. This list also contains the 30 verbs we used to construct the $\mathrm{TM}_{i,t}^{\mathrm{Adaptation}}$ measure in Section 4.5.1.

[17]In Appendix 4.10.2, we describe how we applied these two models to our dataset.

[18]We also constructed similar proxies for $D_{i,t-1}^{Adaptation2}$ and $D_{i,t-1}^{No\ Adaptation2}$ when using the outcomes of text classifications provided by the models. Specifically, a firm was classified as implementing climate adaptation strategies if over 50% of sentences in its annual report, containing terms from the physical climate risk dictionary, were identified as climate adaptation-related by GPT-4 or GPT-4o. The results, available upon request, corroborate the main outcomes about firm value and climate adaptation disclosure that we find when estimating eq. (4.2).

to the results in Table 4.3, we find that only the coefficient β_4 in eq. (4.2) was statistically significant at the 5% level when using either the GPT-4 (column (1)) or GPT-4o (column (2)) model. Overall, the combined evidence from the last two validation tests mitigates the possibility that the results in Table 4.3 are influenced by factors other than the impact of climate adaptation disclosure on firm value.

A fourth potential concern is that the results in Table 4.3 may be driven by multicollinearity. Table A.4.10 reports the correlations between the main regressors in eq. (4.2) over the 1,000 specifications described above. The correlations are generally low in absolute value, suggesting multicollinearity does not appear to be a driving factor in our main results.

A fifth concern is that the results on climate adaptation disclosure may be time-varying. To address this concern, we split the sample into two distinct periods: before and after the introduction of the UK Climate Change Act 2008 (CCA 2008). As explained in section 4.2, this legislation introduced both legally binding emission reduction targets at the country level and the *Adaptation Reporting Power* (Bowen and Rydge, 2011). Consequently, the post-CCA 2008 period is expected to feature greater investor awareness of climate change dynamics and the relevance of corporate climate strategies. Table A.4.11 reports the results for the two subperiods (i.e., before and after the CCA 2008). We find that, both before and after the CCA 2008, investors do not reward firms affected by a natural disaster for disclosing climate adaptation strategies, suggesting persistent challenges in interpreting and valuing this type of disclosure. In contrast, physical climate risk disclosure becomes more positively associated with market-adjusted returns after 2008, consistent with the notion that investors increasingly price physical climate risks in the post-legislation period. This temporal split therefore confirms that, while climate adaptation disclosures remain difficult to evaluate, the relevance of physical risk information has strengthened following the institutionalisation of climate policy.

4.8 Conclusions

This study examines how investors price climate adaptation disclosures by UK firms exposed to natural disasters. We find that firms disclosing their exposure to physical climate risks experience smaller market penalties during disaster events, consistent with the idea that transparent risk disclosure can mitigate information asymmetry and stabilise investor expectations (Guay and Verrecchia, 2018). In contrast, firms that disclose adaptation strategies do not experience similar benefits. Our evidence suggests that adaptation-related information currently fails to reduce investor uncertainty, likely because such disclosures are heterogeneous and difficult to interpret in terms of financial fundamentals.

These findings carry important implications for climate-related financial disclosure policy. First, they support the case for mandatory disclosure of physical climate risks, which appears to achieve the intended policy objective of reducing uncertainty and improving market resilience during climate shocks. By enhancing the transparency of firms' exposures, such disclosures can help stabilise liquidity (Diamond and Verrecchia, 1991) and protect firm value during natural disaster events. This outcome aligns with ongoing international regulatory efforts, including the Task Force on Climate-related Financial Disclosures (TCFD), the UK Green Finance Strategy, and the EU's Corporate Sustainability Reporting Directive (CSRD), all of which aim to improve market efficiency by embedding consistent risk information within corporate reporting frameworks (Goldstein and Yang, 2019).

The second implication of our study is to identify the potential features that disclosure design policies related to climate adaptation should incorporate to reduce investors' uncertainty regarding this information. We frame this implication by conducting a potential cost-benefit analysis of mandatory disclosure of climate adaptation, considering the more general predictions from information disclosure models. In particular, one strand of these models predicts that a mandatory disclosure framework, offering guidance to enhance the precision of information that was previously voluntary, may lead to an improvement in social welfare (Admati and Pfleiderer, 2000). On the other hand, other studies caution against possible unintended consequences of disclosure regulation, such as less informative prices (Banerjee et al., 2018), crowding-out effects on private learning about firm fundamentals (Goldstein and Yang, 2017), and undesirable real consequences (Goldstein and Yang, 2019). As explained by Banerjee et al. (2018), the main consideration in assessing this cost-benefit analysis is to examine whether investors employ the information intended to become publicly available for fundamental or speculative purposes. Our analyses suggest that the penalty imposed by investors on firms disclosing climate adaptation is not motivated by speculative reasons but, rather, by the ambiguous implications of this information when assessing companies' fundamentals following a natural disaster.

Therefore, if the uncertainty reasons about firm fundamentals prevail, regulators should prioritise three design principles: standardisation, comparability, and verifiability. Standardisation would ensure that firms report climate adaptation actions using consistent terminology and metrics (e.g., scenario-based risk assessments and resilience indicators), enabling investors to make comparisons across firms. Comparability requires aligning disclosure templates with established frameworks, such as the TCFD's "Strategy" pillar, which requires firms to explain how climate risks and opportunities affect business models and financial planning over different horizons. Finally, verifiability entails the inclusion of third-party assurance and the use of auditable performance indicators, ensuring that disclosed adaptation measures reflect genuine resilience rather than symbolic compliance.

Overall, our findings suggest that well-designed mandatory disclosure of physical climate risks can reduce information asymmetry and stabilise markets, but that climate adaptation disclosures demand a more sophisticated framework. Regulators should thus move beyond mandating disclosure per se and focus on creating a credible system in which adaptation information is standardised, comparable, and verifiable. The findings of our paper underscore the necessity for such policy measures to be employed within financial markets.

4.9 Figures and Tables

Figure 4.1: Cumulative Abnormal Returns around Natural Disaster Events (Domestic Exposure at the Second Administrative Level – First Climate Adaptation Proxy). This figure shows the daily average cumulative market-adjusted returns of U.K. firms around natural disasters dates. For this analysis, we retained only natural disasters that met each of the following criteria: (i) their duration was less than 30 days, and (ii) they caused at least £100 million in damage, as reported by EM-DAT (in 2018 CPI-adjusted values). In this figure, we define a company as impacted if its headquarter was located in an area affected by a natural disaster on a given date at the second administrative level in the UK. We use the first definition of climate adaptation variable to construct the groups of climate adaptation and no-adaptation firms. Impacted low disclosing firms are represented by the solid line. Impacted firms that disclose physical climate risks only are represented by the dashed line. Impacted firms disclosing climate adaptation are represented by the dotted line. The solid vertical grey line corresponds to the day on which a U.K. firm is hit by a natural disaster.

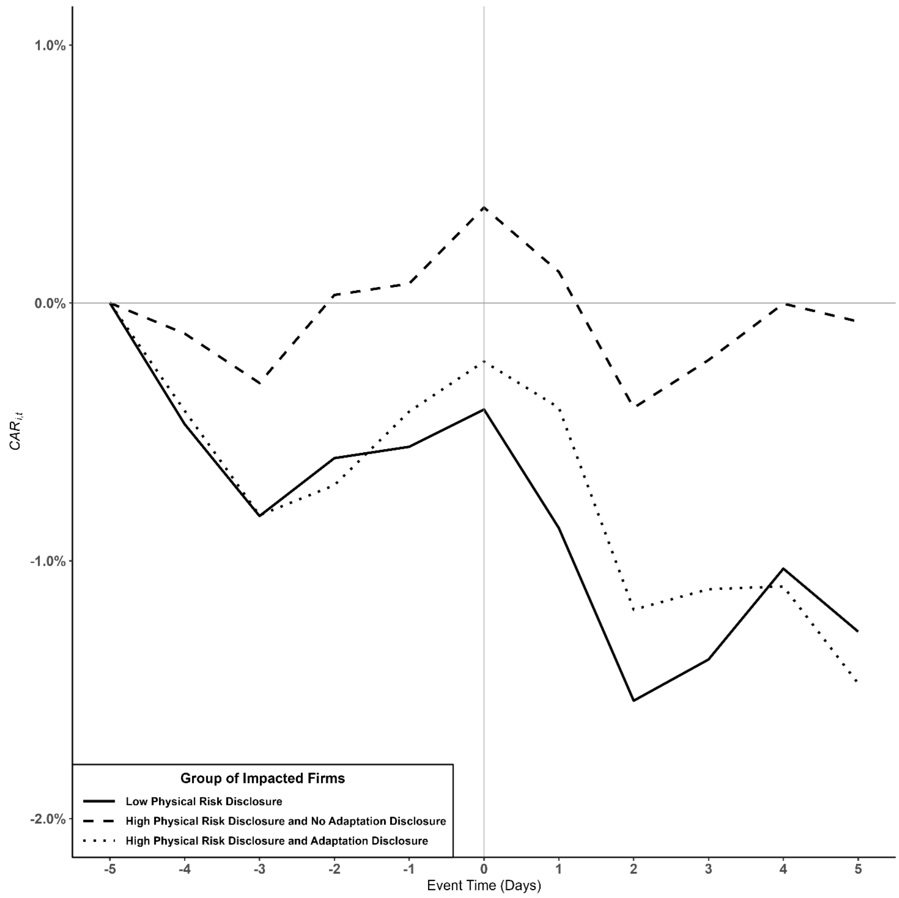


Table 4.1: Summary Statistics. This table reports the summary statistics for the variables used in this study. Textual data was retrieved from Thomson Reuters DataStream and Companies House. Financial data was obtained data from Worldscope, FAME, and Compustat Global. Natural disaster data was obtained by spatially merging information from FAME and GDIS. Sustainable Performance data were obtained from Refinitiv and the Violation Tracker Database UK database. Our initial sample includes all non-financial firms listed on the London Stock Exchange from 1996 to 2018. All continuous variables were winsorised at the 1% and 99% levels. Table A.4.1 provides detailed variable definitions.

Variable	**N**	**Mean**	**S.D.**	**p25**	**Median**	**p75**
Panel A. Textual Data						
$TM^{No\,Adaptation}$	22,542	0.229	0.392	0	0	0.500
$TM^{Adaptation}$	22,542	0.071	0.213	0	0	0
$D^{Adaptation(I)}$	22,542	0.141	0.348	0	0	0
$D^{Adaptation(II)}$	22,542	0.048	0.213	0	0	0
Panel B. Financial Data						
$\log(TA)$	22,542	11.202	2.174	9.715	11.022	12.558
PPE	22,542	0.266	0.256	0.053	0.184	0.407
ROA	22,542	-0.050	0.318	-0.040	0.035	0.079
$CapEx$	22,542	0.049	0.057	0.012	0.031	0.064
$Leverage$	22,542	0.192	0.206	0.019	0.148	0.288
Panel C. Natural and Sustainable Performances Data						
$D^{Impacted(HQ,\ ADL2)}$	22,542	0.056	0.230	0	0	0
ESG	3,498	45.360	18.632	30.940	44.790	58.170
ENV	3,491	38.946	25.514	17.995	37.350	58.055
$D^{Violation}$	7,398	0.011	0.105	0	0	0

Table 4.2: Validation of the climate adaptation and no-adaptation measures. This table examines whether the climate adaptation and no-adaptation measures capture differences in future real-business activities and sustainability performances across firms. In column (1), the dependent variable is represented by capital expenditures in year $t+1$, divided by total assets of the same year $\text{CapEx}_{i,t+1}$. In column (2), the dependent variable is represented by research and development expenditures in year $t+1$, divided by total assets of the same year $\text{R\&D}_{i,t+1}$. In column (3), the dependent variable is the Refinitiv's ESG Overall Score in year $t+1$ $\text{ESG}_{i,t+1}$. In column (4), the dependent variable is the Refinitiv's Environment Pillar Score in year $t+1$ $\text{ENV}_{i,t+1}$. In column (5), the dependent variable is a dummy variable taking the value of one if a firm committed at least one environmental violation in year $t+1$, $D^{\text{Violation}}_{i,t+1}$. Table A.4.1 defines all variables in detail. Firm-level control variables include Log (TA), PPE, CapEx, Leverage and ROA. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$CapEx_{i,t+1}$	$R\&D_{i,t+1}$	$ESG_{i,t+1}$	$ENV_{i,t+1}$	$D^{Violation}_{i,t+1}$
Specification:	(1)	(2)	(3)	(4)	(5)
$TM^{Adaptation}_{i,t}$	0.003**	0.007**	1.500***	1.342*	-0.003
	(2.168)	(2.391)	(2.785)	(1.926)	(-0.393)
$TM^{No\,Adaptation}_{i,t}$	-0.001	0.001	0.773	-0.013	-0.004
	(-0.988)	(0.611)	(1.310)	(-0.016)	(-1.278)
$\log(TA)_{i,t}$	-0.002*	-0.012***	2.463***	4.201***	0.000
	(-1.830)	(-4.211)	(3.180)	(3.124)	(0.072)
$PPE_{i,t}$	-0.016**	-0.005	4.226	-1.234	-0.014
	(-2.186)	(-0.305)	(1.119)	(-0.144)	(-1.727)
$CapEx_{i,t}$	0.280***	-0.016	3.016	0.761	0.018
	(11.233)	(-0.265)	(0.680)	(0.074)	(0.660)
$Leverage_{i,t}$	-0.018***	-0.006	2.949	0.256	0.007
	(-6.144)	(-0.372)	(1.192)	(0.067)	(1.123)
$ROA_{i,t}$	0.010***	-0.045***	5.407**	2.005	-0.002
	(5.117)	(-5.081)	(2.124)	(0.450)	(-1.326)
Obs.	20,119	8,228	3,427	3,421	7,398
R^2 Adj.	0.548	0.707	0.808	0.780	0.344
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Table 4.3: Reaction of market-adjusted returns to natural disasters from 1996 to 2018 (Different Climate Adaptation Proxies). This table examines stock market reactions to natural disasters that occurred at the second-level administrative division in the UK, using different methodologies to construct climate adaptation variables. Details of the event studies are presented in Table 3.3. In all columns, the dependent variable is the cumulative market-adjusted returns for the treatment and control firms from five days before to five days after the natural disaster event, $\text{CAR}_{i,t}[-5,+5]$. In column (1), we use the first definition of the climate adaptation dummy variable to construct $D^{Adaptation1}_{i,t-1}$ and $D^{No\ Adaptation1}_{i,t-1}$. In column (2), we use the second definition of the climate adaptation dummy variable to construct $D^{Adaptation2}_{i,t-1}$ and $D^{No\ Adaptation2}_{i,t-1}$. Firm-level control variables include Log (TA), B/M, ROA and CapEx. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.4.1 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	$CAR_{i,t}[-5,+5]$	
Specification:	(1)	(2)
$D^{\text{Impacted(HQ)}}_{it}$	-0.023***	-0.023***
	(-5.023)	(-5.025)
$D^{\text{No Adaptation1}}_{it-1}$	0.002	
	(0.661)	
$D^{\text{Adaptation1}}_{it-1}$	0.003	
	(0.917)	
$D^{\text{Impacted(HQ)}}_{it} \times D^{\text{No Adaptation1}}_{it-1}$	0.017***	
	(4.354)	
$D^{\text{Impacted(HQ)}}_{it} \times D^{\text{Adaptation1}}_{it-1}$	0.005	
	(0.447)	
$D^{\text{No Adaptation2}}_{it-1}$		0.002
		(0.683)
$D^{\text{Adaptation2}}_{it-1}$		0.006
		(1.148)
$D^{\text{Impacted(HQ)}}_{it} \times D^{\text{No Adaptation2}}_{it-1}$		0.014**
		(2.372)
$D^{\text{Impacted(HQ)}}_{it} \times D^{\text{Adaptation2}}_{it-1}$		-0.011
		(-0.897)
Obs.	11,535	11,535
R^2 Adj.	0.030	0.030
Controls	YES	YES
Firm FE	YES	YES

Table 4.4: Expected cash flows and volatility change analysis around natural disaster events in the UK. This table reports the effect of natural disasters occurring in the UK at the second administrative level on the change in analysts' earnings per share (EPS) forecasts and daily stock return volatility. Details of the event studies are presented in Table 3.3. In all columns, we define a firm as treated if its headquarter is located in a second administrative area affected by a natural disaster on a given date in the UK. In columns (1) and (2), the dependent variable Downgrade$_i$ equals one if the mean consensus in forecasted EPS for the fiscal-year end when a natural disaster happened decreases from 20 trading days before to 20 trading days after a natural disaster, and zero otherwise. In columns (3) and (4), the dependent variable is the percentage change in daily stock return volatility from before to after a natural disaster event, denoted $\Delta\text{Vol}_{i,t}$. The post-event period was defined as one month after a natural disaster event, and the pre-event period was defined as the same post-event period one year before the event. In columns (1) and (3), we use the first definition of the climate adaptation dummy variable to construct $D^{Adaptation1}_{i,t-1}$ and $D^{No\ Adaptation1}_{i,t-1}$. In columns (2) and (4), we use the second definition to construct $D^{Adaptation2}_{i,t-1}$ and $D^{No\ Adaptation2}_{i,t-1}$. Firm-level control variables include Log (TA), B/M, ROA, and CapEx. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.4.1 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	*Downgrade$_i$*		*Δ Vol$_i$*	
Specification:	(1)	(2)	(3)	(4)
D^{Impacted}_{it}	0.003	0.003	-0.018	-0.019
	(0.151)	(0.153)	(-0.222)	(-0.224)
$D^{\text{No Adaptation1}}_{it-1}$	-0.023		0.033	
	(-0.704)		(0.429)	
$D^{\text{Adaptation1}}_{it-1}$	-0.038		0.019	
	(-0.832)		(0.224)	
$D^{\text{Impacted}}_{it} \times D^{\text{No Adaptation1}}_{it-1}$	-0.014		-0.161	
	(-0.202)		(-1.531)	
$D^{\text{Impacted}}_{it} \times D^{\text{Adaptation1}}_{it-1}$	0.015		0.116	
	(0.359)		(0.625)	
$D^{\text{No Adaptation2}}_{it-1}$		-0.027		0.010
		(-0.784)		(0.125)
$D^{\text{Adaptation2}}_{it-1}$		-0.043		0.167
		(-0.768)		(0.847)
$D^{\text{Impacted}}_{it} \times D^{\text{No Adaptation2}}_{it-1}$		0.003		-0.051
		(0.058)		(-0.409)
$D^{\text{Impacted}}_{it} \times D^{\text{Adaptation2}}_{it-1}$		-0.077		-0.030
		(-0.737)		(-0.103)
Obs.	8,307	8,307	11,000	11,000
R^2 Adj.	0.142	0.142	0.149	0.149
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Table 4.5: Regression results of daily closing spread and trading volume changes around natural disaster events in the UK. This table reports the effect of natural disasters occurring in the UK at the second administrative level on daily closing spreads and daily trading volume. Details of the event studies are presented in Table 3.3. In all columns, we define a firm as treated if its headquarter is located in a second administrative area affected by a natural disaster on a given date in the UK. In columns (1) and (2), the dependent variable is the change in closing spread from before to after a natural disaster event, expressed as a percentage. Closing spreads are calculated as in Chung & Zhang (2014). In columns (3) and (4), the dependent variable is the change in British-pound trading volume from before to after a natural disaster event, also expressed as a percentage. In all columns, the post-event period is defined as one month after a natural disaster event, and the pre-event period is defined as the same post-event period one year before the event. In columns (1) and (3), we use the first definition of the climate adaptation dummy variable to construct $D^{Adaptation1}_{i,t-1}$ and $D^{No\ Adaptation1}_{i,t-1}$. In columns (2) and (4), we use the second definition to construct $D^{Adaptation2}_{i,t-1}$ and $D^{No\ Adaptation2}_{i,t-1}$. Firm-level control variables include Log (TA), B/M, ROA, CapEx, and ΔVol$_i$. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.4.1 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	$\Delta Closing\ Spread_i$		$\Delta Trading\ Volume_i$	
Specification:	(1)	(2)	(3)	(4)
$D^{\text{Impacted(HQ)}}_{it}$	0.185***	0.185***	-1.076***	-1.076***
	(3.053)	(3.052)	(-4.422)	(-4.431)
$D^{\text{No Adaptation}}_{it-1}$	-0.063		-0.464	
	(-0.933)		(-1.256)	
$D^{\text{Adaptation1}}_{it-1}$	-0.028		-0.072	
	(-0.364)		(-0.210)	
$D^{\text{Impacted(HQ)}}_{it} \times D^{\text{No Adaptation1}}_{it-1}$	-0.092**		1.012***	
	(-2.404)		(3.542)	
$D^{\text{Impacted(HQ)}}_{it} \times D^{\text{Adaptation1}}_{it-1}$	-0.028		0.360	
	(-0.534)		(1.246)	
$D^{\text{No Adaptation2}}_{it-1}$		-0.062		-0.322
		(-0.949)		(-0.965)
$D^{\text{Adaptation2}}_{it-1}$		0.018		-0.571
		(0.175)		(-1.498)
$D^{\text{Impacted(HQ)}}_{it} \times D^{\text{No Adaptation2}}_{it-1}$		-0.076**		0.775***
		(-2.033)		(2.997)
$D^{\text{Impacted(HQ)}}_{it} \times D^{\text{Adaptation2}}_{it-1}$		0.041		0.435
		(0.241)		(0.791)
Obs.	11,000	11,000	10,944	10,944
R^2 Adj.	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Volatility Control	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Table 4.6: Regression results of market-adjusted returns, daily closing spread and trading volume changes around natural disaster events in the UK, split by industry competition. This table reports the effect of natural disasters occurring in the UK at the second administrative level on market-adjusted returns, daily closing spreads, and daily trading volume for firms operating in competitive and non-competitive industries separately. Details of the event studies are presented in Table 3.3. In columns (1) and (2), the dependent variable is the cumulative market-adjusted returns for the treatment and control firms from five days before to five days after the natural disaster event ($\text{CAR}_{i,t}[-5,+5]$). In columns (3) and (4), the dependent variable is the change in closing spread from before to after a natural disaster event in percentage. Closing spread are calculated as in Chung and Zhang (2014). In columns (5) and (6), the dependent variable is the change in British-pound trading volume from before to after a natural disaster event in percentage. Columns (1), (3) and (5) report the results for firms operating in not-competitive industries. Columns (2), (4) and (6) report the results for firms operating in competitive industries. A firm is considered to operate in a competitive (not-competitive) environment in a given year if its industry's HHI falls below (above) the median value of the HHI distribution calculated for that year. In all columns, we use the first definition of climate adaptation dummy variable to construct $D_{i,t-1}^{Adaptation1}$ and $D_{i,t-1}^{No\ Adaptation1}$. In all columns, firm-level control variables include Log (TA), B/M, ROA, CapEx. Columns (3)-(6) also include ΔVol_i. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.4.1 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	$CAR_{i,t}[-5,+5]$		$\Delta Closing\ Spread_i$		$\Delta Trading\ Volume_i$	
Detail of Affected Area (UK): *ADL2*						
Type of Industry:	Not Competitive		Competitive		Not Competitive	Competitive
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
$D_{i,t}^{Impacted(HQ)}$	-0.022***	-0.025***	0.127***	0.212***	-1.178**	-1.200***
	(-2.803)	(-4.436)	(2.625)	(2.946)	(-2.186)	(-3.256)
$D_{i,t-1}^{No\ Adaptation1}$	-0.006	0.006	-0.056	-0.088	-2.028	-0.203
	(-0.707)	(1.477)	(-0.714)	(-0.996)	(-1.451)	(-0.435)
$D_{i,t-1}^{Adaptation1}$	0.001	0.004	-0.138	0.014	-1.309	0.071
	(0.141)	(0.910)	(-1.422)	(0.173)	(-1.533)	(0.186)
$D_{i,t}^{Impacted(HQ)} \times D_{i,t-1}^{No\ Adaptation1}$	0.017	0.018***	0.017	-0.118***	0.960*	1.149***
	(1.047)	(2.908)	(0.155)	(-2.643)	(1.753)	(2.801)
$D_{i,t}^{Impacted(HQ)} \times D_{i,t-1}^{Adaptation1}$	0.012	0.001	-0.029	-0.055	0.784	0.318
	(0.816)	(0.065)	(-0.255)	(-0.649)	(1.013)	(0.502)
Obs.	2,670	8,265	2,560	8,440	2,434	7,660
R2 Adj.	0.005	0.038	0.212	0.214	0.268	0.211
Controls	YES	YES	YES	YES	YES	YES
Volatility Control	NO	NO	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

4.10 Appendix

4.10.1 Additional Tables

Table A.4.1: Variable Definitions. This table describes the variables used in our analyses and their respective sources. Data sources are: CG = Compustat Global; CH = Companies House; DS = Thomson Reuters DataStream; F = FAME; G = GDIS; IBES = Institutional Brokers' Estimate System; R = Refinitiv; TRE = Thomson Reuters Eikon; V = Violation Tracker Database UK; W = Worldscope; WS = WRDS European Short Data.

Variable	**Definition and Sources**
$TM^{High\,Exposure}$	The frequency of unigrams or bigrams related to our physical climate risk dictionary in a generic annual report, divided by the number of words in the annual report. (Sources: TRE, CH).
$D^{High\,Exposure}$	A dummy variable taking the value of one if the firm average value for $TM^{High\,Exposure}$ is greater than the sample average value. (Sources: TRE, CH).
$TM^{Adaptation}$	The frequency of unigrams or bigrams related to our physical climate risk dictionary in a generic annual report in the proximity of climate adaptation verbs, divided by the number of physical climate risk words in an annual report. (Source: TRE, CH)
$TM^{No\ Adaptation}$	The frequency of unigrams or bigrams related to our physical climate risk dictionary in a generic annual report not appearing in the proximity of climate adaptation verbs, divided by the number of physical climate risk words in an annual report. (Source: TRE, CH)
$D^{\text{Adaptation (I)}}$	A dummy taking the value of one if $TM^{Adaptation}$ is greater than zero. (Source: TRE, CH)

Variable	**Definition and Sources**
$D^{\text{Adaptation (II)}}$	A dummy taking the value of one if $TM^{Adaptation}$ is greater than 50%. (Source: TRE, CH)
$D^{Adaptation1}$	A dummy variable taking the value of one if $D^{High\,Exposure}$=1 and $D^{\text{Adaptation (I)}}$=1. (Source: TRE, CH)
$D^{No\ Adaptation1}$	A dummy variable taking the value of one if $D^{High\,Exposure}$=1 and $D^{\text{Adaptation (I)}}$=0. (Source: TRE, CH)
$D^{Adaptation2}$	A dummy variable taking the value of one if $D^{High\,Exposure}$=1 and $D^{\text{Adaptation (II)}}$=1. (Source: TRE, CH)
$D^{No\ Adaptation2}$	A dummy variable taking the value of one if $D^{High\,Exposure}$=1 and $D^{\text{Adaptation (II)}}$=0. (Source: TRE, CH)
$D^{Impacted(HQ)}$	A dummy taking the value of one if the firm headquarter is located in an affected area in the UK at a given time. (Sources: F, G).
CAR[-5,+5]	Cumulative market-adjusted returns for treatment and control firms from five days before to five days after the natural disaster event. (Sources: DS).
Δ*Closing Spread*	The difference in bid-ask spreads in percentage over a one-month period following a natural disaster event and during the same calendar time window in the previous year. (Sources: DS).
Δ*Trading Volume*	The difference in British-pound trading volume in percentage over a one-month period following a natural disaster event and during the same calendar time window in the previous year. (Sources: DS).
Δ*Vol*	The difference in volatility of daily stock returns in percentage over a one-month period following a natural disaster event and during the same calendar time window in the previous year. (Sources: DS).

Variable	**Definition and Sources**
Downgrade	A dummy variable taking the value of one if the mean consensus in forecasted EPS for the fiscal-year end when a natural disaster happened decreases from 20 trading days before to 20 trading days after a natural disaster. (Sources: IBES).
ΔROA	The change in net income divided by total assets from the year before to one year after a natural disaster. (Sources: W, F, CG).
D^{Short}	A dummy variable taking the value of one if at least one institutional investor short-sells a firm from five days before to five days after the natural disaster event. (Sources: WS).
Log(TA)	Natural logarithm of firm's total assets. (Sources: W, F, CG).
PPE/TA	Property, plant and equipment, divided by total assets of the same year. (Sources: W, F, CG).
B/M	Book value of shareholder equity, divided by the market capitalisation at the end of the fiscal year. (Sources: W, F, CG).
ROA	Net income, divided by total assets of the same year. (Sources: W, F, CG).
CapEx	Capital Expenditures, divided by total assets of the same year. (Sources: W, F, CG).
Leverage	Total debt (short-term debt and long-term debt), divided by the total asset. (Sources: W, F, CG).
R&D	Research and development expenditures, divided by total assets of the same year. (Sources: W, F, CG).
ESG	Refinitiv's ESG Overall Score. (Source: R)
ENV	Refinitiv's Environment Pillar Score. (Source: R)
$D^{Violation}$	A dummy variable taking the value of one if a firm committed at least one environmental violation. (Source: V)

Table A.4.2: Top-100 climate-related keywords in the proximity of climate adaptation verbs. This table reports the top 100 unigrams or bigrams associated with $\text{TM}^{\text{High Exposure}}$ (see Chapter 3), appearing in the proximity of climate adaptation verbs. Table A.4.1 defines all variables in detail.

Unigram/Bigram	N	Unigram/Bigram	N	Unigram/Bigram	N
weather	9730	the tornado	79	of rain	46
temperature	4404	storms in	75	the rainy	45
flooding	1711	of storm	73	the rain	45
temperatures	1273	soil erosion	71	perfect storm	45
rainfall	1191	hurricanes in	68	wetter	44
drought	755	of flood	66	unseasonably warm	44
floods	493	hurricanes and	66	dry summer	44
subsidence	259	winter conditions	65	snowfall	44
poor summer	203	for typhoon	64	flood damage	43
the flood	188	coldest	62	exceptionally cold	43
the storm	187	storm damage	62	of snow	42
mild winter	170	droughts	61	to flood	41
hot summer	156	hurricane season	60	very wet	41
typhoon and	152	rains and	60	the storms	40
storm and	151	storm costs	60	by lightning	40
the typhoon	149	heavy rains	58	very hot	39
colder	148	snow in	58	hurricane sandy	39
flood risk	142	wet summer	58	cold season	39
severe winter	130	flood at	57	storm of	39
and flood	123	by hurricane	56	dry season	38
wettest	116	rainy season	55	very cold	38
cold winter	111	as hurricanes	55	storm in	37
unseasonal	105	flood or	52	rain and	37
major storms	100	water flood	52	tornado and	37
hurricane katrina	91	heavy rain	52	wildfires	36
flood and	91	hurricane harvey	51	exceptionally hot	36
the snow	89	and snow	50	very warm	36
dry periods	87	extreme cold	50	or flood	35
of typhoon	84	the hurricanes	49	and hurricane	34
snow and	84	wet season	49	extra cold	34
lightning strikes	82	storms and	48	and tornado	34
and storm	82	dry conditions	48	heating season	34
the hurricane	81	harsh winter	47	and rain	34
of hurricane	80				

Table A.4.3: Industry patterns of the physical climate risk and adaptation measures. This table reports firms' physical climate risk and climate adaptation measures for the top 10 industries. Statistics are reported at the firm-year level across different supersectors according to the ICB classification system. $\text{TM}^{\text{Adaptation}}$ measures the frequency of such terms appearing in the proximity of climate adaptation verbs, normalized by the number of climate risk words in the report. $D^{\text{Adaptation (I)}}$ is a dummy equal to one if $\text{TM}^{\text{Adaptation}} > 0$, and zero otherwise. $D^{\text{Adaptation (II)}}$ is a dummy equal to one if $\text{TM}^{\text{Adaptation}}$ exceeds 50%. Table A.4.1 defines all variables in detail.

Panel A: $\text{TM}^{\text{Adaptation}}$			
Supersector (ICB)	**Mean**	**S.D.**	**N**
Utilities	0.174	0.233	382
Chemicals	0.142	0.271	412
Construction and Materials	0.126	0.271	833
Energy	0.119	0.272	1036
Food, Beverage and Tobacco	0.110	0.227	233
Basic Resources	0.108	0.236	388
Automobiles and Parts	0.088	0.244	110
Travel and Leisure	0.078	0.226	1662
Personal Care, Drug and Grocery Stores	0.073	0.226	387
Industrial Goods and Services	0.073	0.211	5307
Panel B: $D^{\text{Adaptation (I)}}$			
Supersector (ICB)	**Mean**	**S.D.**	**N**
Utilities	0.516	0.500	382
Food, Beverage and Tobacco	0.325	0.469	233
Chemicals	0.303	0.460	412
Basic Resources	0.260	0.442	388
Energy	0.232	0.422	1036
Construction and Materials	0.217	0.413	833
Travel and Leisure	0.161	0.368	1662
Industrial Goods and Services	0.149	0.356	5307
Personal Care, Drug and Grocery Stores	0.147	0.355	387
Telecommunications	0.145	0.352	539
Panel C: $D^{\text{Adaptation (II)}}$			
Supersector (ICB)	**Mean**	**S.D.**	**N**
Construction and Materials	0.091	0.287	833
Chemicals	0.083	0.275	412
Energy	0.083	0.276	1036
Utilities	0.080	0.269	382
Automobiles and Parts	0.064	0.245	110
Basic Resources	0.061	0.239	388
Food, Beverage and Tobacco	0.057	0.236	778
Personal Care, Drug and Grocery Stores	0.057	0.232	387
Retail	0.055	0.229	1262
Travel and Leisure	0.050	0.218	1662

Table A.4.4: Excerpts in UK annual reports with the highest climate adaptation measures. This table presents excerpts from UK annual reports with the highest values of the climate adaptation measures. These excerpts are text fragments extracted from the portion of each annual report where the algorithm identifies the discussion of physical climate risk keywords in the proximity of climate adaptation verbs. Physical climate risk keywords are highlighted in *italic*, while climate adaptation verbs are highlighted in **bold**. We also report the year of the annual report and the firm's industry affiliation according to the ICB classification system.

Firm	Supersector	Year	Text surrounding physical climate risk keywords (*italic*) and adaptation verbs (bold)
Anglo American PLC	Basic Resources	2015	Our *Capcoal*, Dawson and Moranbah North mines in the Bowen Basin, Queensland, have **invested** a combined $110 million in better on-site water management, including extensive pump and piping works, improved *flood protection* infrastructure, road-sheeting works, and upgrades to underground mines, drainage network, storage and dewatering capacity.
Aurelian Oil & Gas PLC	Energy	2010	During the year the Company also **invested** €0.3 million on its tangible assets, largely on refinements to its *Bilca* production asset to **protect** it from the *flooding* it has experienced in recent years.
Albert Fisher Group PLC	Food, Beverage and Tobacco	1999	*Frost damage* to Californian citrus limited sales of this key product line but, as a consequence, alternative Spanish sourcing has been established which will **ensure** better security of supply in future years.
Treatt PLC	Chemicals	2018	The site expansion project includes an upgrade to the existing buildings to **improve** their ability to withstand *storm damage*, including a complete replacement of the roof to the older of the two existing buildings.
Severn Trent PLC	Utilities	2003	We will also be able to **meet** other new challenges, such as the protection of some householders from sewer *flooding*. Our efforts to **provide** a top quality service to our customers were recognised when we won a Customer Care Award at the Utility Industry Achievement Awards for the success of measures to tackle sewer *flooding*. Reduced the environmental impact of our trucks by switching the entire fleet to ultra low sulphur diesel, the cleanest mass-market fuel available, ensuring the new Skelton Grange site can **provide** continuous service in wet and windy *weather* when other landfills may close.

Table A.4.5: Realized cash flows and short-selling activity analysis around natural disaster events in the UK. This table reports the effect of natural disasters in the UK at the second administrative level on firms' future accounting performance and the short-selling activity of institutional investors. In columns (1) and (2), the dependent variable is the change in earnings divided by total assets from the year before to one year after a natural disaster, denoted ΔROA_i. In columns (3) and (4), the dependent variable $D_{i,t}^{\text{Short}}$ equals one if at least one institutional investor short-sells a firm during the $[-5, +5]$ window. In columns (1) and (3), we use the first definition of the climate adaptation dummy to construct $D_{i,t-1}^{\text{Adaptation1}}$ and $D_{i,t-1}^{\text{No Adaptation1}}$. In columns (2) and (4), we use the second definition to construct $D_{i,t-1}^{\text{Adaptation2}}$ and $D_{i,t-1}^{\text{No Adaptation2}}$. In columns (1) and (2), firm-level control variables include Log (TA), B/M, and CapEx. In columns (3) and (4), control variables include Log (TA), ROA, B/M, and CapEx. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.4.1 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ΔROA_i		D_i^{Short}	
Specification:	(1)	(2)	(3)	(4)
D_{it}^{Impacted}	-0.006	-0.006	-0.018	-0.018
	(-1.007)	(-1.011)	(-0.902)	(-0.904)
$D_{it-1}^{\text{No Adaptation1}}$	0.002		-0.017	
	(0.164)		(-0.414)	
$D_{it-1}^{\text{Adaptation1}}$	-0.014		0.007	
	(-1.210)		(0.160)	
$D_{it}^{\text{Impacted}} \times D_{it-1}^{\text{No Adaptation1}}$	0.008		-0.056	
	(0.887)		(-0.886)	
$D_{it}^{\text{Impacted}} \times D_{it-1}^{\text{Adaptation1}}$	0.006		0.067	
	(0.339)		(1.012)	
$D_{it-1}^{\text{No Adaptation2}}$		-0.002		-0.011
		(-0.191)		(-0.271)
$D_{it-1}^{\text{Adaptation2}}$		-0.011		0.061
		(-0.601)		(1.220)
$D_{it}^{\text{Impacted}} \times D_{it-1}^{\text{No Adaptation2}}$		0.011		-0.010
		(1.195)		(-0.170)
$D_{it}^{\text{Impacted}} \times D_{it-1}^{\text{Adaptation2}}$		-0.033		-0.038
		(-0.676)		(-0.867)
Obs.	11,277	11,277	2,308	2,308
R^2 Adj.	0.334	0.334	0.422	0.422
Controls	YES	YES	YES	YES
ROA Control	NO	NO	YES	YES
Firm FE	YES	YES	YES	YES

Table A.4.6: Reaction of market-adjusted returns to natural disasters from 1996 to 2018 (Domestic Exposure – Different Climate Adaptation Proxies – Triple DiD Specification). This table examines stock market reactions to natural disasters that occurred at the second-level administrative division in the UK, using different variables to measure climate adaptation at the firm level. In all columns, the dependent variable is the cumulative market-adjusted return for treatment and control firms from five days before to five days after the natural disaster event, denoted $\text{CAR}_{i,t}[-5,+5]$. In column (1), we use the climate adaptation ratio $\text{TM}^{\text{Adaptation}}_{i,t-1}$ to measure firm-level adaptation. In column (2), we use the first definition of the climate adaptation dummy $D^{\text{Adaptation(I)}}_{i,t-1}$. In column (3), we use the second definition $D^{\text{Adaptation(II)}}_{i,t-1}$. Firm-level control variables include Log (TA), B/M, ROA, and CapEx. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.4.1 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	$CAR_{i,[-5,+5]}$		
Specification:	(1)	(2)	(3)
D^{Impacted}_{it}	-0.022***	-0.023***	-0.023***
	(-5.003)	(-4.948)	(-5.010)
$D^{\text{High Exposure}}_{it-1}$	0.002	0.003	0.002
	(0.654)	(0.696)	(0.666)
$TM^{\text{Adaptation}}_{it-1}$	0.000		
	(0.035)		
$D^{\text{Impacted}}_{it} \times D^{\text{High Exposure}}_{it-1}$	0.016***	0.017***	0.014**
	(3.174)	(4.312)	(2.373)
$D^{\text{Impacted}}_{it} \times TM^{\text{Adaptation}}_{it-1}$	-0.009		
	(-0.678)		
$D^{\text{High Exposure}}_{it-1} \times TM^{\text{Adaptation}}_{it-1}$	0.002		
	(0.222)		
$D^{\text{Impacted}}_{it} \times D^{\text{High Exposure}}_{it-1} \times TM^{\text{Adaptation}}_{it-1}$	-0.020		
	(-1.218)		
$D^{\text{Adaptation(I)}}_{it-1}$		0.001	
		(0.203)	
$D^{\text{Impacted}}_{it} \times D^{\text{Adaptation(I)}}_{it-1}$		-0.003	
		(-0.385)	
$D^{\text{High Exposure}}_{it-1} \times D^{\text{Adaptation(I)}}_{it-1}$		0.000	
		(0.013)	
$D^{\text{Impacted}}_{it} \times D^{\text{High Exposure}}_{it-1} \times D^{\text{Adaptation(I)}}_{it-1}$		-0.009	
		(-0.649)	
$D^{\text{Adaptation(II)}}_{it-1}$			-0.000
			(-0.132)
$D^{\text{Impacted}}_{it} \times D^{\text{Adaptation(II)}}_{it-1}$			-0.009
			(-0.544)
$D^{\text{High Exposure}}_{it-1} \times D^{\text{Adaptation(II)}}_{it-1}$			0.004
			(0.536)
$D^{\text{Impacted}}_{it} \times D^{\text{High Exposure}}_{it-1} \times D^{\text{Adaptation(II)}}_{it-1}$			-0.017
			(-0.978)
Obs.	11,535	11,535	11,535
R^2 Adj.	0.030	0.030	0.030
Controls	YES	YES	YES
Firm FE	YES	YES	YES

Table A.4.7: Placebo Tests. This table examines stock market reactions to two placebo dates for natural disasters that occurred at the second-level administrative division in the UK, using different methodologies to construct climate adaptation variables. In all columns, the dependent variable is the cumulative market-adjusted return for treatment and control firms over the $[-5,+5]$ period. In columns (1) and (2), we assign a false disaster date 30 calendar days before the actual event. In columns (3) and (4), the false date is set 30 calendar days after the true event. In columns (1) and (3), we use the first definition of the climate adaptation dummy to construct $D_{i,t-1}^{\text{Adaptation1}}$ and $D_{i,t-1}^{\text{No Adaptation1}}$. In columns (2) and (4), we use the second definition to construct $D_{i,t-1}^{\text{Adaptation2}}$ and $D_{i,t-1}^{\text{No Adaptation2}}$. Firm-level control variables include Log (TA), B/M, ROA, and CapEx. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.4.1 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	$CAR_{i,[-5,+5]}$			
Placebo Dates:	30 days before the event		30 days after the event	
Specification:	(1)	(2)	(3)	(4)
$D_{i,t}^{\text{Impacted}}$	0.018	0.018	-0.007	-0.007
	(1.555)	(1.557)	(-1.285)	(-1.287)
$D_{i,t-1}^{\text{No Adaptation1}}$	0.006		-0.001	
	(1.167)		(-0.286)	
$D_{i,t-1}^{\text{Adaptation1}}$	0.003		-0.002	
	(0.630)		(-0.437)	
$D_{i,t}^{\text{Impacted}} \times D_{i,t-1}^{\text{No Adaptation1}}$	-0.000		0.003	
	(-0.017)		(0.787)	
$D_{i,t}^{\text{Impacted}} \times D_{i,t-1}^{\text{Adaptation1}}$	-0.004		0.002	
	(-0.567)		(0.447)	
$D_{i,t-1}^{\text{No Adaptation2}}$		0.007		-0.001
		(1.348)		(-0.422)
$D_{i,t-1}^{\text{Adaptation2}}$		-0.008		0.001
		(-1.350)		(0.285)
$D_{i,t}^{\text{Impacted}} \times D_{i,t-1}^{\text{No Adaptation2}}$		-0.003		0.005
		(-0.397)		(1.447)
$D_{i,t}^{\text{Impacted}} \times D_{i,t-1}^{\text{Adaptation2}}$		0.021		-0.019
		(1.498)		(-0.985)
Obs.	11,491	11,491	11,525	11,525
R^2 Adj.	0.051	0.052	0.044	0.044
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Table A.4.8: Sensitivity analysis of market-adjusted returns with different climate adaptation specifications. This table reports the percentage of significant beta coefficients for the two main regressors in Equation (4). We created 1,000 combinations to build the $\text{TM}_{i,t}^{\text{Adaptation}}$ variable—used to construct the $D_{i,t}^{\text{Adaptation}}$ and $D_{i,t}^{\text{No Adaptation}}$ measures—by considering two non-mutually exclusive options. First, we randomly selected 30, 40, or 50 climate adaptation verbs from a pool of 190 verbs identified using the procedure described in Section 5.1. Second, we varied the textual proximity window in which adaptation verbs and physical climate risk terms must co-occur, considering: (i) the same sentence, (ii) the same and following sentences, and (iii) the previous, same, and following sentences. The first row of the table presents results for β_4 in Equation (4), while the second row presents results for β_5. A coefficient is considered statistically significant if it reaches at least the 5% level. In column (1), we use the first definition of the climate adaptation dummy to construct $D_{i,t-1}^{\text{Adaptation1}}$ and $D_{i,t-1}^{\text{No Adaptation1}}$. In column (2), we use the second definition to construct $D_{i,t-1}^{\text{Adaptation2}}$ and $D_{i,t-1}^{\text{No Adaptation2}}$. Table A.4.1 defines all variables in detail.

Dependent Variable:	$CAR_{i,[-5,+5]}$	
Coefficient	(1)	(2)
β_4	99%	95.7%
β_5	0.4%	14.6%

Table A.4.9: Stock market reactions to natural disasters using GPT-based climate adaptation classifications. This table examines stock market reactions to natural disasters that occurred at the second-level administrative division in the UK, using OpenAI's GPT-4 and GPT-4o models to construct climate adaptation variables. In all columns, the dependent variable is the cumulative market-adjusted return for the treatment and control firms from five days before to five days after the natural disaster event, denoted $\text{CAR}_{i,t}[-5,+5]$. In column (1), we use the text classification provided by GPT-4 and the first definition of the climate adaptation dummy to construct $D^{\text{Adaptation1}}_{i,t-1}$ and $D^{\text{No Adaptation1}}_{i,t-1}$. In column (2), we use the classification from GPT-4o with the same definition of climate adaptation. Firm-level control variables include Log (TA), B/M, ROA, and CapEx. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.4.1 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	$CAR_{i,t}[-5,+5]$	
Model used for text classification:	GPT-4	GPT-4o
Specification:	(1)	(2)
$D^{\text{Impacted(HQ)}}_{i,t}$	-0.023***	-0.023***
	(-5.017)	(-5.014)
$D^{\text{No Adaptation1}}_{i,t-1}$	0.003	0.003
	(0.848)	(0.801)
$D^{\text{Adaptation1}}_{i,t-1}$	0.003	0.004
	(0.630)	(0.588)
$D^{\text{Impacted(HQ)}}_{i,t} \times D^{\text{No Adaptation1}}_{i,t-1}$	0.012**	0.014**
	(2.151)	(2.451)
$D^{\text{Impacted(HQ)}}_{i,t} \times D^{\text{Adaptation1}}_{i,t-1}$	0.010	-0.002
	(1.396)	(-0.473)
Obs.	11,535	11,535
R^2 Adj.	0.030	0.030
Controls	YES	YES
Firm FE	YES	YES

Table A.4.10: Correlation Matrix for text mining dummies in eq. (4.2)**.** This table shows the Pearson correlation coefficients for the main variables in eq. (4.2). We created 1,000 combinations to build the $\text{TM}_{i,t}^{\text{Adaptation}}$ variable (which we use to construct the $D_{i,t}^{\text{Adaptation}}$ $D_{i,t}^{\text{No Adaptation}}$ measures by considering two non-mutually exclusive options. First, we constructed the $\text{TM}_{i,t}^{\text{Adaptation}}$ variable considering 30, 40, or 50 climate adaptation verbs randomly selected from a list of 190 verbs retrieved via the procedure explained in Section 4.5.1. With respect to the second option, we constructed the $\text{TM}_{i,t}^{\text{Adaptation}}$ variable considering climate adaptation verbs appearing in: i) the same sentence; ii) the same and the following sentences; iii) the previous, the same and the following sentences where physical climate terms appear. In Panel A, we use the first definition of climate adaptation dummy variable to construct $D_{i,t-1}^{Adaptation1}$ and $D_{i,t-1}^{No\ Adaptation1}$. In Panel B, we use the second definition of climate adaptation dummy variable to construct $D_{i,t-1}^{Adaptation2}$ and $D_{i,t-1}^{No\ Adaptation2}$. Table A.4.1 defines all variables in detail.

Panel A: First climate adaptation specification

	$D_{i,t}^{\text{Impacted}}$	$D_{i,t-1}^{\text{No Adaptation1}}$	$D_{i,t-1}^{\text{Adaptation1}}$	$D_{i,t-1}^{\text{No Adaptation1}} \cdot D_{i,t}^{\text{Impacted}}$	$D_{i,t-1}^{\text{Adaptation1}} \cdot D_{i,t}^{\text{Impacted}}$
$D_{i,t}^{\text{Impacted}}$	1	-0.002	-0.002	0.374	0.287
$D_{i,t-1}^{\text{No Adaptation1}}$		1	-0.138	0.315	-0.045
$D_{i,t-1}^{\text{Adaptation1}}$			1	-0.044	0.324
$D_{i,t-1}^{\text{No Adaptation1}} \cdot D_{i,t}^{\text{Impacted}}$				1	-0.014
$D_{i,t-1}^{\text{Adaptation1}} \cdot D_{i,t}^{\text{Impacted}}$					1

Panel B: Second climate adaptation specification

	$D_{i,t}^{\text{Impacted}}$	$D_{i,t-1}^{\text{No Adaptation2}}$	$D_{i,t-1}^{\text{Adaptation2}}$	$D_{i,t-1}^{\text{No Adaptation2}} \cdot D_{i,t}^{\text{Impacted}}$	$D_{i,t-1}^{\text{Adaptation2}} \cdot D_{i,t}^{\text{Impacted}}$
$D_{i,t}^{\text{Impacted}}$	1	-0.001	-0.004	0.454	0.135
$D_{i,t-1}^{\text{No Adaptation2}}$		1	-0.082	0.303	-0.027
$D_{i,t-1}^{\text{Adaptation2}}$			1	-0.025	0.324
$D_{i,t-1}^{\text{No Adaptation2}} \cdot D_{i,t}^{\text{Impacted}}$				1	-0.008
$D_{i,t-1}^{\text{Adaptation2}} \cdot D_{i,t}^{\text{Impacted}}$					1

Table A.4.11: Reaction of market-adjusted returns to natural disasters in two different sample periods (Different Climate Adaptation Proxies). This table examines stock market reactions to natural disasters at the second-level administrative division in the UK across two different sample periods, using alternative methodologies to construct climate adaptation variables. In all columns, the dependent variable is the cumulative market-adjusted return for treatment and control firms over the $[-5, +5]$ window. In columns (1) and (2), the sample period covers the years prior to the establishment of the Climate Change Act 2008 (CCA 2008) (i.e., 1996–2007). In columns (3) and (4), the sample period covers the years following the establishment of the Climate Change Act 2008 (i.e., 2008–2018). In columns (1) and (3), we use the first definition of the climate adaptation dummy to construct $D_{i,t-1}^{\text{Adaptation1}}$ and $D_{i,t-1}^{\text{No Adaptation1}}$. In columns (2) and (4), we use the second definition to construct $D_{i,t-1}^{\text{Adaptation2}}$ and $D_{i,t-1}^{\text{No Adaptation2}}$. Firm-level control variables include Log (TA), B/M, ROA, and CapEx. All continuous variables are winsorised at the 1% and 99% levels. t-statistics are reported in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.4.1 defines all variables in detail. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	$CAR_{i,[-5,+5]}$			
Sample Period:	Before CCA 2008		After CCA 2008	
Specification:	(1)	(2)	(3)	(4)
$D_{i,t}^{\text{Impacted}}$	-0.022**	-0.022**	-0.031***	-0.031***
	(-2.520)	(-2.513)	(-3.564)	(-3.563)
$D_{i,t-1}^{\text{No Adaptation1}}$	0.024		0.009	
	(1.424)		(0.618)	
$D_{i,t-1}^{\text{Adaptation1}}$	0.010		0.002	
	(1.597)		(0.125)	
$D_{i,t}^{\text{Impacted}} \times D_{i,t-1}^{\text{No Adaptation1}}$	0.011*		0.021***	
	(1.756)		(0.946)	
$D_{i,t}^{\text{Impacted}} \times D_{i,t-1}^{\text{Adaptation1}}$	0.011		0.010	
	(0.798)		(0.949)	
$D_{i,t-1}^{\text{No Adaptation2}}$		0.006		-0.008
		(0.328)		(-0.752)
$D_{i,t-1}^{\text{Adaptation2}}$		0.012		0.004
		(1.124)		(0.278)
$D_{i,t}^{\text{Impacted}} \times D_{i,t-1}^{\text{No Adaptation2}}$		0.009*		0.017**
		(1.784)		(2.440)
$D_{i,t}^{\text{Impacted}} \times D_{i,t-1}^{\text{Adaptation2}}$		0.008		0.012
		(1.017)		(1.002)
Num. Obs.	6,656	6,656	4,879	4,879
R^2 Adj.	0.072	0.072	0.031	0.031
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

4.10.2 Classifying Climate Adaptation Disclosure using Open AI's GPT-4 and GPT-4o

In this Appendix, we describe how we employed GPT-4 and GPT-4o, the spearhead products of OpenAI at the time of writing, to classify climate adaptation in companies' annual reports. We also analyse the classification performances of our selected list of verbs (i.e., the keyword-based approach) with those provided by these two models.

Using advanced models like GPT-4 or GPT-4o to classify climate adaptation from companies' annual reports comes with both advantages and disadvantages. The main advantage is that, unlike traditional keyword-based approaches that rely on a fixed list of words (e.g., verbs), these models can perform a *semantic* analysis of sentences to identify whether a firm is discussing climate adaptation. This is possible because both GPT-4 and GPT-4o were trained on a large amount of internet texts (including articles, books, annual reports and websites), which helps these models to comprehend a wide array of topics, including corporate responses to physical climate risks. However, there are two main disadvantages in using these models. First, the cost of using GPT-4 to classify a large sample of annual reports like ours can be high. Second, the time and computational resources needed to process large datasets are significant.

We took these advantages and disadvantages into account when applying the following steps to use GPT-4 and GPT-4o on our dataset[19]. In the first step, we extracted all sentences from the sample of annual reports that contained terms from the physical climate risk dictionary introduced in Section 4.5.1. Focussing only on this sub-sample of sentences is important for two reasons. First, this allows us to optimise costs and decrease computation

[19]The following steps are based on previous literature that compares the textual classification results of machine learning models and keyword-based approaches with human classifications (see, for instance, Bingler et al. (2024) and Schimanski et al. (2023), among others).

time. Second, these sentences are used to classify climate adaptation in corporate annual reports with our list of climate-adaptation verbs. Therefore, these sentences provide a natural benchmark to compare the classification performances of GPT-4 and GPT-4o with our keyword-based approach.

In the second step, we provided GPT-4 and GPT-4o with a prompt for "zero-shot" classification to determine if a sentence indicates adaptation to physical climate risks. Importantly, we based this classification on the definition of "climate adaptation" provided by the Intergovernmental Panel on Climate Change.[20] The prompt provided was as follows:

> """ Your task is to classify excerpts from companies' annual statements and determine whether they indicate the company is undertaking climate adaptation to physical climate risks or not.
>
> The climate adaptation definition you should use in this task is the following: "Adaptation [to physical climate risks] represents the process of adjustment to actual or expected climate and its effects. In human systems, adaptation seeks to moderate or avoid harm or exploit beneficial opportunities."[21]
>
> As output, you must say "yes" if the company is doing climate adaptation to physical climate risks, and you must say "no" if it isn't. You must also provide the degree of confidence in your classification expressed as a probability, i.e. a number from 0 to 1.
>
> For example, the output for a sentence for which you are 90% confident should be: yes, 0.9. """

We considered as climate-adaptation related only those sentences for which either GPT-4 or GPT4-o provided a score higher than 80%.

In the third step, we compared the classification outcomes provided by GPT-4 and GPT-4o with those from our list of climate-adaptation verbs. For this purpose, we draw a sample of 100 sentences containing terms from the physical climate risk dictionary. We then manually labelled sentences as "yes" if these sentences indicated corporate adaptation to physical climate risks, and as "no" if that was not the case. To assess the classification outcomes of

[20] For more information, see `https://www.ipcc.ch/site/assets/uploads/2019/01/SYRAR5-Glossary_en.pdf`

[21] We added the term "[to physical climate risks]" to the IPCC definition to make it more specific and relevant to the type of analysis we conduct in the paper.

the different approaches, we used four standard performance metrics: accuracy, precision, recall, and F1 score. Table A.4.12 reports the results. As can be seen from the Table, our approach based on the list of climate adaptation verbs achieves the highest values across all metrics. Of particular interest is the fact that our approach achieves high precision (0.83), meaning that it makes slightly fewer false positive mistakes than GPT-4o (0.81) or GPT-4 (0.80).[22] This is a desirable feature because climate adaptation disclosures are relatively few among all physical climate risk disclosures, making the measured climate adaptation efforts sensitive to false positive errors. Considering that all methods achieve good accuracy, the higher precision makes our approach more suitable for this study. However, in our robustness tests shown in Table A.4.12, we re-estimated our baseline regression results using the text classifications provided by GPT-4 and GPT-4o and found consistent results with our keyword-based approach.

[22]We acknowledge that the classification outcomes of both GPT-4 and GPT-4o could be improved by applying a fine-tuning procedure to both models. However, the high costs and computation time required for this procedure, combined with the good performance achieved by our approach, make fine-tuning less relevant for our study.

Table A.4.12: Evaluation results for the classification tasks of the list of climate adaptation verbs, GPT-4 and GPT-4o. This table reports the classification results of different approaches used to classify climate adaptation in a random sample of 100 sentences containing physical climate risk terms. Accuracy is the number of correct classifications divided by the number of all classifications made. Precision is the number of true positives divided by the sum of true positives and false positives. Recall is the number of true positives divided by the sum of true positives and false negatives. F1 score is the harmonic mean of precision and recall.

Approach	Accuracy	Precision	Recall	F1 Score
List of Climate Adaptation Verbs	0.89	0.83	0.73	0.78
GPT-4o	0.88	0.81	0.69	0.75
GPT-4	0.87	0.80	0.65	0.72

Chapter 5

Green Money Talks: Responsible Ownership and Disclosure of Material Climate Commitments

5.1 Introduction

Climate change represents a defining challenge for the global financial system, with profound implications for asset valuation, capital allocation, and long-term economic stability. As the threats of a low-carbon economic and global warming intensify, firms are increasingly expected to provide detailed information to their shareholders about the strategies to deal with the effects of climate change (Flammer et al., 2021). Among the shareholders interested in this information, responsible institutional investors, such as those that are signatories of the UN PRI framework, play a crucial role, given that such disclosures represent a key input into their valuation models and stewardship decisions. However, despite the growing influence of these types of investors in recent years, there is still limited empirical evidence on whether they elicit firms to voluntarily disclose material information about climate commitments. Moreover, it remains unknown whether such engagement leads firms to release disclosures that are not only more detailed, but also informative and useful to other market participants.

In this paper, we address these questions by constructing a novel dataset that combines several sources of textual, responsible ownership and financial information. First, we leverage the state-of-the-art capabilities of a domain-specific large language model introduced in Bingler et al. (2024), *ClimateBERT*, to classify disclosures of material climate-related commitments in UK annual reports. Importantly, we further refine the classifications provided by *ClimateBERT* to distinguish between those material commitments targeting transition risks from those addressing physical climate risks (Wagner et al., 2023). These classifications allow us to differentiate, for example, between specific mitigation commitments to reduce carbon emissions (i.e., climate transition-risk related) from detailed adaptation commitments against flood risk (i.e., climate physical-risk related). We then merge this data with information about responsible stock (traditional) ownership, the latter defined as the fraction of firm shares owned by institutional shareholders who are (not) UN PRI signatories. This allows us to analyse whether UN PRI investors actively engage and pressure portfolio firms to voluntarily disclose this information. Finally, we examine the capital market consequences of disclosures induced by UN PRI investors by analysing absolute cumulative abnormal returns (CAR) around filing dates of annual reports and analysts' earnings per share (EPS) forecast accuracy at different horizons. Using these data, we contribute to the climate finance literature in the following ways.

Our first contribution is the finding that responsible (rather than traditional) ownership plays a key role in driving firms to voluntarily disclose material commitments to address climate change risks. For example, a one-standard-deviation increase in ownership by UN PRI investors is associated with a 0.12-unit increase in the natural logarithm of one plus the number of material climate commitments in an annual report, or about 9% of the variable's mean. Notably, all our estimations account for other important drivers of a firm's voluntary decision to disclose material climate commitments, by controlling for the firm sustainability performances and the decisions to sign climate disclosure initiatives such as the Task Force on Climate-related Financial Disclosures. Moreover, additional empirical tests support a causal interpretation of our baseline findings. First, we employ an instrumental variable approach using FTSE 350 index membership as an instrument for UN PRI ownership. The idea underlying this identification strategy is that stocks are added *mechanically* to the FTSE 350 index because of their relative free-float-adjusted market capitalization, and not because of their levels of disclosure about material climate commitments. We find that instrumented UN PRI ownership predicts firms' decisions to disclose material climate commitments. Second, we exploit the 2013–2014 fiduciary duty clarification in the UK as a quasi-natural experiment. This reform clarified stewardship obligations of UK institutional investors, providing a source of exogenous variation in responsible investor engagement. Using a difference-in-differences specification, we find that, following the reform, UK-domiciled UN PRI signatories became more influential in eliciting disclosures of material climate commitments from investee firms relative to UK non-signatory investors. These findings contribute to the growing literature on institutional investors and corporate climate disclosure (Ilhan et al., 2023a; Black et al., 2024) by demonstrating that responsible investors do not merely screen or tilt their portfolios, but engage in stewardship that affects the information environment of their investee firms.

Our second contribution is the finding that the positive relationship between responsible ownership and disclosure is primarily driven by material commitments about climate transition risk, rather than against physical climate risks. In particular, when we disaggregate the disclosure measure by climate risk type, we find that our baseline results and causal estimates are concentrated towards transition-climate commitments. This asymmetry has important implications for climate governance. Specifically, our findings align with recent studies that challenge the adequacy of market-based mechanisms alone to ensure voluntary firm transparency about climate strategies, especially in the domain of climate adaptation. We contribute to this literature by strengthening the case for *mandatory* mandates aimed at improving transparency around physical climate risks.

Our third contribution is to show that the disclosures of material climate commitments demanded by UN PRI investors convey *new* information in capital markets. To study this, we exploit variation in disclosure generated by the interaction between UN PRI ownership and FTSE 350 index membership, an exogenous source of investor pressure driven by market capitalization and unrelated to annual report timing and analyst forecast periods. Using this strategy, we first show that the instrumented disclosure measure of material climate commitments is associated with positive absolute abnormal stock returns around annual report releases. Moreover, we find that the instrumented disclosure measure leads to lower analyst forecast errors, especially over longer horizons. Notably, in both tests we find that the detected effect is driven by material commitments against transition risk, consistent with the notion that shareholders and analysts pay particular attention to disclosures arising from UN PRI investors engagements. Overall, these results are consistent with the literature documenting the informational content of voluntary sustainable disclosures (e.g., Ben-Amar et al. (2024)), and they further refine our understanding by identifying investor-driven materiality as a key mechanism through which these benefits arise.

The remainder of the paper is organised as follows. Section 5.2 presents our hypotheses. Section 5.3 describes the data. Section 5.4 presents the baseline results, while Section 5.5 our identification tests. Section 5.6 presents the capital market tests. Finally, Section 5.7 provides concluding remarks.

5.2 Hypothesis Development

Institutional investors increasingly incorporate climate-related information into their capital allocation decisions, motivated by both fiduciary responsibilities and long-term risk management concerns (Ilhan et al., 2023a). Within this group, responsible investors, particularly those affiliated with the UN PRI framework, have explicitly committed to integrating environmental, social, and governance (ESG) considerations into their investment processes. Climate-related disclosures, and in particular, those that concern material commitments against climate change risks, serve as a key input in such assessments. These disclosures can reduce information asymmetries, facilitate risk pricing, and enhance portfolio alignment with long-term decarbonization targets. Therefore, if responsible investors are to fulfil their mandates, it is critical that they elicit material and credible climate-related information from their investee firms.

A core tenet of responsible investing is precisely this form of active engagement of UN PRI investors to enhance ESG-related transparency. This is in fact explicitly codified in the UN-PRI framework: Principle 3 states that "*We will seek appropriate disclosure on ESG issues by the entities in which we invest*". This formal commitment suggests that UN PRI-affiliated investors do not merely integrate ESG factors into their analyses passively but actively push for the disclosure of ESG-relevant information, including climate-related commitments that can be considered material under financial reporting standards. Empirical literature supports this view. For instance, Black et al. (2024) show that UN PRI investor engagement on ESG issues, when successful, improves both disclosure and sustainable performance outcomes. Similarly, Ilhan et al. (2023a) find that climate-conscious institutional investors consider climate risks financially material and are increasingly engaging with firms to enhance climate-related transparency. These findings suggest that the presence of UN PRI investors in a firm's ownership structure may serve as a channel for the voluntary supply of disclosures about material climate commitments. Accordingly, we posit the following hypothesis:

H1*: UN PRI investors demand disclosure of material climate commitments to their investee firms.*

Climate risks are typically decomposed into two primary dimensions: transition risks, which arises from regulatory, technological, and market shifts associated with the move toward a low-carbon economy; and physical risk, which reflects exposure to acute and chronic climate-related events (Wagner et al., 2023). While both climate risks are financially material, a growing body of survey evidence suggests that institutional investors pay more attention to transition risks, given their systematic nature and potential to affect asset valuations across sectors and geographies (Harnett, 2017; Krueger et al., 2020). Consistent with this notion, recent anecdotal evidence in financial markets indicates that responsible investors actively engage with portfolio firms to reduce carbon-related exposure and elicit greater disclosures of strategic responses to climate transition risks. A prominent example is the Climate Action 100+ initiative, a coalition of over 600 institutional investors representing more than $60 trillion in assets under management, which has pushed high-emitting firms to articulate net-zero targets, publish credible decarbonization pathways, and embed climate oversight into corporate governance structures. In contrast, investor engagement on physical climate risks remains far more limited. Initiatives focused on climate adaptation, such as CDP's water security disclosures or the UNEP's Principles for Sustainable Insurance, have witnessed low institutional uptake, and lack the structured coordination and enforcement mechanisms that characterise transition-focused investor campaigns. Taken together, these patterns suggest that responsible investors are more likely to demand disclosure of material climate commitments that are more readily integrated into investment decision-making processes. This leads us to formulate our second hypothesis:

H2: *UN PRI investors are more interested in demanding disclosure of material climate commitments against climate transition risks rather than towards physical climate risks.*

A central assumption in financial economics is that disclosure has information content to the extent that it conveys new, decision-relevant information to market participants (Verrecchia, 2001). When investors demand disclosure of material climate commitments, they are signalling that the absence of such information impedes their ability to assess firm value accurately. This is especially relevant for responsible investors, whose integration of ESG factors into investment analysis relies on reliable information to inform forecasts, asset allocation, and risk pricing. The notion of information content thus suggests that climate-related disclosures, especially when elicited by investor demand and perceived as credible, should elicit market reactions. From a market microstructure perspective, such disclosures may mitigate information asymmetries surrounding firms' fundamental values, particularly around key information events such as the release of annual reports (Tsang et al., 2019). Furthermore, to the extent that these disclosures reduce uncertainty regarding future cash flows, regulatory risks, and capital investment needs, they may enhance analysts' information environment and thereby improve the accuracy of earnings forecasts across multiple horizons. This leads us to the formulation of the following two hypotheses:

H3A: *UN PRI investor-driven disclosure of material climate commitments increases the information content of a firm annual report.*

H3B: *UN PRI investor-driven disclosure of material climate commitments contains information content that is relevant for equity research analysts.*

5.3 Data

We now explain the three main sources of data used to build the measures required to test our hypotheses. We then describe the selection of control variables used in the regression analysis.

5.3.1 Material Climate Commitments Data from Annual Reports

To measure the level of disclosure of material climate commitments in UK annual reports, we use a novel methodology based on ClimateBERT (Bingler et al., 2024).[1] ClimateBERT is a family of language models adapted from BERT (Bidirectional Encoder Representations from Transformers) and fine-tuned on climate-related text including scientific literature, policy documents, and corporate annual reports. These models are further fine-tuned for certain classification tasks relevant to identify climate-related content, detecting climate commitments, and assessing the specificity of climate-related disclosures (Bingler et al., 2024; Wagner et al., 2023). Importantly, by capturing semantic context in climate-related language, ClimateBERT offers improvements over traditional dictionary-based methods in measuring the materiality of climate commitments in companies' annual reports.

The construction of the disclosure measures employed in this study relies on a sequence of classification steps, each using a task-specific ClimateBERT model. First, for a given paragraph in an annual report, we apply a ClimateBERT classifier to determine whether the paragraph is climate-related. If so, we use a second classifier to assess whether it contains a corporate climate commitment. Finally, for paragraphs identified as climate commitment-related, we apply a third ClimateBERT model to classify whether the com-

[1] The dataset of annual reports was constructed following the approach described in Chapter 3 and Chapter 4.

mitment is *specific* or generic. Therefore, we use the concept of 'specificity' as defined in Bingler et al. (2024) to proxy for the materiality of climate commitments.[2] Finally, to distinguish between material climate *transition* risk commitments from material climate *physical* risk commitments, we rely on a fourth ClimateBERT classification algorithm developed in Wagner et al. (2023). The last classification allows us to distinguish, for example, between climate mitigation commitments to reduce carbon emissions (i.e., climate transition-risk related) from corporate adaptation commitments to adapt against flood risk (i.e., climate physical-risk related).

Using these ClimateBERT classifications, we create three measures to proxy for the intensity of disclosure about material climate commitments at the firm level. The first measure, *Specific CC Commitments*, is the natural logarithm of one plus the number of paragraphs in a firm annual report classified from ClimateBERT as specific commitments against climate risks. The other two measures, *Specific TR Commitments* and *Specific PR Commitments*, are similarly defined but focus on paragraphs related to either climate transition risks, or climate physical risks, respectively. Summary statistics for these variables are reported in Table 5.1. The mean value of *Specific CC Commitments* is 1.3, meaning that the average firm in our sample discloses around 3 specific climate commitments in its annual report. When analysing the sub-components of climate risks, we find that the mean of *Specific TR Commitments* is of 0.92, while *Specific PR Commitments* has a mean of 0.081. The fact that firms are more inclined to voluntarily report on material climate transition-risk commitments rather than climate physical risk commitments is consistent with the survey evidence in Tang (2022). In particular, one of the reasons why disclosure of commitments against physical climate risks is

[2] In Bingler et al. (2024), a paragraph containing a climate-related commitment is classified as "specific" if it contains detailed performance information, details of actions, or tangible and verifiable targets. Bingler et al. (2024) emphasises that materiality ultimately depends on the interpretation of the user (e.g., investors). However, our capital market tests suggest that such specific information, especially when demanded by responsible investors, is likely to be material to market participants.

low is that most stakeholders of UK firms want to know the management approach for reducing emissions, rather than corporate strategies to adapt to physical climate risks.

5.3.2 Responsible Ownership

We measure responsible institutional ownership of UK firms by combining data from the Thomson Reuters Ownership database with information on institutional signatories to the UN PRI. The Thomson Reuters Ownership database reports institutional equity holdings, retrieved from regulatory filings (e.g., share register disclosures to the FCA), fund company reports, and other public disclosures. We match the names of institutional investors in the UN PRI dataset to those in the Thomson Reuters Ownership database. Given that the two datasets do not share a common identifier, we use fuzzy matching techniques to perform the match.[3] Based on these matches, we define *responsible investors* as those that are UN PRI signatories, and *traditional* investors as those that are not.

Table 5.1, Panel B, presents summary statistics on the equity ownership of responsible and traditional institutional investors. On average, traditional (non-UN PRI) investors hold a larger share of firm equity (mean = 27%) than responsible (UN PRI signatory) investors (mean = 13%). The median ownership follows a similar pattern (25% vs. 6.1%), highlighting that UN PRI investors, while present across many firms, tend to hold smaller stakes. This ownership structure is relevant for our analysis, as it implies that UN PRI investors may face constraints in exerting direct pressure on investee firms. Nevertheless, even with lower average holdings, responsible investors may still influence corporate climate disclosure if their engagements are targeted and strategic (Dimson et al., 2023). Our empirical analysis investigates the effects of such responsible investors' engagement in influencing the level of

[3]Supplementary Appendix in Section 5.9.2 provides detailed documentation of the matching procedure.

specific climate commitment in the annual reports of their investee firms.

5.3.3 Annual Reports Filing Returns and EPS Accuracy Data

We obtain additional data to construct two measures aimed at examining whether the disclosure of specific climate commitments, as required by UN PRI investors, is perceived material by the market. The first measure, $CAR[-1,1]$, is the absolute cumulative abnormal return over a three-day window around the filing date of an annual report. Because information on the exact filing dates of annual reports is not available in Thomson Reuters Eikon or Companies House, we retrieved these dates by retrieving data from the *Investegate* platform.[4] Specifically, we first downloaded all announcements and their corresponding dates for each firm during our sample period. We then retained, for each firm-year observation, only those announcements that included the term 'annual report' in their title or description. Table 5.1 shows that the mean value of $CAR[-1,1]$ is 3.7% (and a median of 2.1%), indicating that the release of a firm annual report typically contains substantial information content for investors.

The second measure is equity analysts' earnings per shares (EPS) accuracy at different horizons. To construct this measure, we first retrieved from IBES historical data about the mean consensus EPS forecasts for the current fiscal year, one-year ahead and two-years ahead. We then measured the analyst earnings forecast accuracy annually using forecast error, computed as the average value of absolute difference between monthly mean earnings forecasts and actual earnings, divided by stock price at the beginning of the year. Summary statistics for these variables are reported in Table 5.1. As expected, the mean forecast error increases monotonically with the forecast horizon. This pattern is consistent with the increasing difficulty analysts

[4] Investigate represents the UK's most comprehensive source of announcements from UK quoted companies. For more information, see: `https://www.investegate.co.uk/welcome`

face in accurately forecasting earnings over longer time periods.

5.3.4 Control Variables

We collect additional data for a range of potentially important factors that, if left uncontrolled, could confound our inferences. We control for these factors by including a battery of firm-specific and climate-related variables.

Climate Disclosure Variables

To better assess the relationship between UN PRI institutional ownership and the disclosure of material climate commitments, we include two climate disclosure variables used in Bingler et al. (2024). The first variable, *Climate Share*, measures the proportion of climate-related paragraphs in a firm's annual report. It captures the overall volume of climate reporting, helping us account for whether UN PRI investors prefer firms that discuss climate issues in general. The second measure is a sentiment climate score, *Opp/Risk*, defined as the logarithm of the ratio between the number of climate-related paragraphs classified as opportunity-focused and those classified as risk-focused. This allows us to control for the tone of climate disclosure, which may influence UN PRI investors' preferences beyond climate disclosure volume.

Climate-related Initiatives

To isolate the relationship between UN PRI ownership and the disclosure of material climate commitments, it is important to control for firm-level participation in voluntary climate-related initiatives. These initiatives often signal a firm's active stance on climate issues and may independently influence both the extent of climate disclosure and the attractiveness of the firm to UN PRI investors. Following Bingler et al. (2024), we retrieve the company lists from the initiatives' websites to determine the signature of the SBT, TCFD, or CA100+ focus companies. The Task Force on Climate-related Financial Disclosures (TCFD) is important in our context as it encourages firms to adopt a standardized and investor-relevant framework for climate risk reporting, directly affecting the quality of disclosure. The Science Based Targets initiative (SBT) signals a firm's commitment to scientifically grounded emissions reductions, which can influence both disclosure depth and perceptions of credibility among UN PRI investors. Climate Action 100+ is particularly relevant as it reflects external investor pressure on high-emitting firms to improve climate governance and transparency, potentially driving disclosure irrespective of responsible ownership structure.

Financial Variables

We retrieved data on financial variables identified in the literature as potentially influencing companies' reporting practices, to serve as control variables. First, we matched the annual report data with firm-level financial data in British pounds (GBP) from Worldscope. We also incorporated information on firms' fiscal year-end reporting dates to ensure precise alignment between financial records and annual report content. Moreover, we excluded all firms classified under the "Financials" sector, based on the Industry Classification Benchmark (ICB). This exclusion ensures that our analysis focuses only on non-financial firms, which are directly exposed to physical and transition climate risks and are therefore more likely to disclose material climate commitments as part of their core operations, rather than as providers of climate-related financial instruments.

Sustainability Performances

Finally, as a further robustness check, we obtain data on firms' sustainability performance from Datastream, specifically focusing on emission intensity and environmental scores. Emission intensity is calculated as the sum of Scope 1 and Scope 2 greenhouse gas emissions scaled by fixed assets. The environmental score corresponds to the industry-adjusted environmental rating reported by Datastream. Differently from all the control variables described so far, data on sustainability performance of firms in our sample are more limited, as UK firms are not uniformly required to disclose corporate emissions. Moreover, environmental scores are selectively provided by third parties.

Given our empirical setting, it is important to note that these variables are more appropriately viewed as post-treatment outcomes rather than pre-treatment confounders. Specifically, including them as controls in our setting may absorb part of the causal effect that operates through firms' sustainable performances, thereby leading to an underestimation of the overall impact of responsible ownership on disclosure of material climate commitments. This concern is supported by a growing literature in climate finance showing that responsible investors exert a causal influence on both firm-level emissions (Liu et al., 2024) and third-party environmental assessments (Dyck et al., 2019).

To study the implication and the relevance of including these two variables in our setting, we first regress a firms' emission intensity and a firm's industry adjusted-environmental scores on lagged responsible and traditional ownership as well as the full set of lagged firm-level controls described in this section. Table A.5.3 report the results of this analysis and shows that *lagged* responsible ownership is negatively associated with emission intensity (column 1) and positively correlated with industry-adjusted environmental scores (column 2). The results in Table A.5.3 thus provides direct evidence that these sustainability outcomes are significantly influenced by responsible investor ownership, confirming their post-treatment nature in our empirical setting. Therefore, including these variables in our following analyses may have the unintended consequence of "controlling away" some of the responsible ownership-related effect we want to measure (giving rise to the known "bad control" problem). In the next section, we further check whether these variables are relevant for disclosure beyond the effect of responsible ownership by using the estimated *residuals* of the two dependent variables in Table A.5.3. These residuals will allow us to capture only the component of each variable that is orthogonal to responsible ownership and other controls variables, thereby isolating variation in sustainability performances that cannot be attributed to the effects of responsible ownership.

5.4 Baseline Results

We begin our investigation of the relationship between UN PRI ownership and disclosure of material climate-related commitments by estimating the following baseline regression model:

$$\text{Specific Commitments}_{i,t} = \beta_1 \text{IO}_{i,t} + X_{i,t} + \theta_i + \vartheta_t + \varepsilon_{i,t} \qquad (5.1)$$

where Specific Commitments$_{i,t}$ represents either the log of one plus the number of paragraphs in a firm annual report classified from ClimateBERT as specific commitments against (i) climate risks in general; (ii) climate transition risks or (iii) climate physical risks. The variable $\text{IO}_{i,t}$ denotes the fraction of firm shares owned by UN PRI institutional at the end of fiscal-year t. $X_{i,t}$ is the vector of control variables defined in Section 5.3.4. We include industry fixed effects and year fixed effects. Standard errors are double clustered at firm and year levels.

Table 5.2 presents the results. In column 1, we find that UN PRI ownership is positively related to the decision of investee firms to disclose specific climate commitments, consistent with Hypothesis 1. Results are not only statistically significant but also economically relevant. For example, in column (1), a one-standard-deviation increase in UN PRI investor ownership is associated with a 0.12-unit increase in log(1 + specific climate commitments), or about 9% of the variable's mean.

Moreover, in columns (2), (4), and (6), where we include the residuals of emission intensity and environmental score (estimated in Table A.5.3), these variables are statistically insignificant, while the coefficient on responsible ownership remains statistically significant (albeit smaller in magnitude).[5] This pattern is consistent with the interpretation that both measures of environmental performance are post-treatment outcomes of responsible ownership and therefore act as "bad controls" when included in raw form. Moreover, this residualisation exercise demonstrates that, once the variation in environmental performance explained by responsible ownership is stripped out, the remaining component has no explanatory power in explaining disclosure. Consequently, we exclude emission intensity and environmental score as controls in our subsequent analyses to avoid post-treatment bias and to retain an unbiased estimate of the effect of responsible ownership on climate-related disclosure.

In columns (3) to (6), we find that the positive relationship between responsible ownership and disclosure is primarily driven by specific commitments about climate transition risk. In column 3, a one-standard-deviation increase in UN PRI investor ownership is associated with a 0.12-unit increase in log(1 + TR specific climate commitments), or about 13% of the variable's mean. On the other hand, we do not find a significant association between responsible ownership and specific physical climate risk commitments. Overall, these results are consistent with Hypothesis 2.

Finally, Table 5.2 also reports interesting results regarding other firm characteristics. First, we do not find a significant relationship between ownership by non-UN PRI institutional investors and the disclosure of specific

[5]As explained in Section 5.3.4, the number of observations differs across columns when we include, as additional control variables, those related to emission intensity and environmental scores.

climate commitments. An exception is column (5), where the relationship is statistically significant and negative, though small in terms of economic significance. Across all specifications, large firms, firms with higher capital intensity and growth firms disclose more. Moreover, firms with high levels of climate change disclosure and those that are signatories of climate-related initiatives tend to disclose more about their specific commitments against climate risks.

5.5 Identification

Our baseline results in Section 5.4 show that UN PRI ownership has a positive effect on firms' decision to disclose specific climate commitments. One potential explanation for this result is direct engagement by UN PRI investors, who may pressure portfolio firms to voluntarily disclose this information. However, identifying the causal effect of responsible ownership on corporate climate disclosure policies remains empirically challenging for several reasons. First, selection effects may be at play: UN PRI investors may tilt their portfolios toward firms that already disclose material climate commitments, either because such firms signal strong risk management practices or because investor mandates require alignment with certain ESG standards. Second, reverse causality is a concern, as firms may adopt detailed climate disclosures to attract or retain capital from ESG-oriented investors, such as institutions that are UN PRI signatories. Finally, omitted variable bias may arise if unobservable firm characteristics (e.g., firm-level ESG expertise) jointly influence UN PRI ownership and firms' disclosure behaviour, thereby biasing OLS estimates in an indeterminate direction.

In this section, we implement empirical strategies to mitigate these sources of endogeneity and strengthen the causal interpretation of our baseline findings. To establish a causal relationship, we need to generate an exogenous shock to UN PRI ownership, while the shock should be unrelated to firms' decision to disclose material commitments against climate risks. In the following two subsections, we explain how we exploited two quasi-natural experiments to generate these kinds of exogenous shocks.

5.5.1 Instrumental Variable Approach

In our first identification strategy we use instrumental variable (IV) regressions to directly address the concerns of selection effect and reverse causality. A large literature in corporate finance ((Boone and White, 2015; Bird and Karolyi, 2016; Dyck et al., 2019), among others) exploit exogenous variation in institutional ownership caused from a firm's stock being added to a major stock market index. In our study, we use stock additions to the FTSE350 index as an instrument for UN PRI ownership. Anecdotal evidence suggests that stock indices such as the FTSE 350 are tracked not only by institutional investors in general, but also by UN PRI signatories in particular. For instance, Rathbones, a UN PRI signatory, has led the "Votes Against Slavery" campaign, which targeted FTSE 350 companies to improve compliance with modern slavery disclosure requirements under UK law. This example illustrates not only that responsible investors do invest in FTSE 350 index firms, but also that they engage with them to influence their ESG-related disclosure practices.[6]

The FTSE350 index represents the performance of the 350 largest companies listed on the London Stock Exchange, combining the FTSE 100 (the 100 largest firms) and the FTSE 250 (the next 250 largest firms) based on market capitalization.[7] Stocks are included in the index according to their

[6] For more information about the "Votes Against Slavery" campaign, see: `https://www.unpri.org/rathbones-votes-against-slavery/9412.article`

[7] Differently from other studies we do not implement a regression discontinuity design (RDD) using FTSE350 index membership because, unlike indices with fixed rank-based cutoffs such as the pre-2006 Russell 1000 and Russel 2000 indices, the FTSE 350 does not have a "clean" threshold for inclusion. Its construction is based on a dynamic combination of the FTSE100 and FTSE250, both of which use buffer zones to smooth transitions and reduce index turnover. This methodology weakens the quasi-random assignment around the index cutoffs that RDD relies on, making it unsuitable for our identification strategy.

free-float-adjusted market capitalization, with periodic reviews to ensure the index can proxy for the performance of the largest firms in the UK stock market. Therefore, stocks are added *mechanically* to the FTSE 350 index because of their relative free-float-adjusted market capitalization, and not because of their levels of disclosure about material climate change commitments. This feature of the FTSE 350 is important to meet the exclusion condition of the instrument in our setting. Other UK stock indices that are more sustainable-focussed, such as the FTSE4Good Index, do not satisfy such condition because a firm's inclusion to the index is based, among other criteria, on the quality of its climate disclosures.[8] This would violate the core assumption of the IV framework that the instrument affects the outcome (i.e., disclosure) only through the endogenous regressor (UN PRI ownership).

Importantly, to further mitigate the concern that FTSE 350 membership may correlate with greater investor scrutiny or disclosure incentives due to firm size or visibility, all IV specifications include the comprehensive set of control variables described in Section 5.3.4. These controls absorb systematic differences between larger and smaller firms that could otherwise confound the exclusion restriction, such as firm size, leverage, profitability, and participation in voluntary climate-related initiatives. Because the instrument varies mechanically with free-float-adjusted market capitalization, and given that size-related effects are already partialled out by the inclusion of relevant control variables, the identifying variation reflects exogenous shifts in responsible ownership induced by index inclusion rather than inherent differences in disclosure propensity.

We report the 2SLS regression results in Table 5.3. Panel A shows the first-stage results. We find that UN PRI investors increase their holdings by about 4.4 percentage points when a firm is added to the FTSE350 Index.

[8] For more information, see, for instance: `https://research.ftserussell.com/products/index-notices/home/getmethodology?id=2599107`

Moreover, the first-stage F-statistic of 50 exceeds the conventional threshold for weak instrument concerns, thereby supporting the relevance condition. More importantly, the second-stage results in Panel B show that *instrumented* responsible ownership is positively and significantly associated to disclosure of specific climate commitments (column 1). Consistent with our baseline findings in Table 5.2, we find that this positive relationship is primarily driven by material commitments towards transition climate risks (column 2), rather than towards physical climate risks (column 3). The results also suggest strong economic impacts. Focusing on the significant coefficients in columns 1 and 2, they imply that a one standard deviation change in UN PRI ownership leads to a 79% change in the amount of specific climate commitments, and to a 84% change in specific climate commitments towards transition risks. Notably, these implied changes in the level of climate disclosure are larger than the implied OLS impacts in Table 5.2. This result is consistent with the idea that the increase in UN PRI ownership driven by the firm index inclusion has a stronger effect on investee firms' disclosure decisions than the average ownership relationship captured in OLS.[9]

To further address issues related to the exclusion restriction of the IV framework, we employ index additions within a DiD framework, where newly indexed firms form the treatment group. The economic intuition here is that, similar to the instrumental variable case, a firm's addition to the index is generally followed by substantial increases in responsible institutional ownership (as previously discussed). This occurs both because index constituent firms gain greater visibility among investors and because many passive portfolio managers need to closely track the FTSE350 Index. We exploit these characteristics to conduct a DiD analysis examining the effect of index additions on firms' disclosure of material climate commitments. For the DiD analysis, we follow Tsang et al. (2019) and employ a five-year window around index

[9]We re-estimated the IV regressions using a restricted sample that includes only firms whose FTSE 350 membership status changed at least once during the sample period. Untabulated results are qualitatively similar to those shown in Table 5.3, mitigating concerns that low time-series variation in the instrument might drive our findings.

additions, with additions occurring between year -1 and year 0. We obtain a sample of index additions for the period 2006–2021. *Post* is coded as 1 for years following the addition event, and 0 otherwise. These index additions constitute our treated firms. Control firms are neighbouring firms from the same year that have the closest value of *IO UN PRI* in year -1. Panel A of Table A.5.4 reports the comparison between treatment and control firms during the pre-treatment period. We find that treatment and control firms have similar values for disclosure variables and no significant differences in *IO UN PRI* and *IO non-UN PRI*, indicating that the two groups are comparable prior to treatment. Panel B of Table A.5.4 reports the results of the DiD regressions. Column (1) shows that, compared with the control group, UN PRI institutional ownership in treated firms increased significantly, on average, by 5.52 per cent around the time a firm was added to the FTSE350. However, the coefficient on *Treated* $\times$ *Post* in column (2) is insignificant, suggesting that, interestingly, there is no corresponding change in *IO non-UN PRI*. More importantly, column (3) shows statistically significant increases in the disclosure of material climate commitments following a firm's addition to the FTSE350 Index. Consistent with previous analyses, we find that the effect is driven by disclosures of material commitments related to climate transition risk (column 4), rather than to physical climate risks (see column 5).

Overall, these results indicate that our baseline findings are not due to the endogenous selection of firms with high levels of disclosure about specific climate commitments. Rather, these results suggest that UN PRI investors demand their investee firms to publicly report this kind of information, particularly with respect to material commitments related to climate transition risks.

5.5.2 Disclosure of Material Climate Commitments and Responsible Ownership: Evidence from the 2013-2014 UK Fiduciary Duty Law

In our second experiment we examine whether increased legal clarity about institutional fiduciary duties induced UN PRI investors to demand disclosure of material climate commitment to their investee firms. Specifically, we analyse the impact of the UK Law Commission's 2013–2014 statement affirming that incorporating ESG factors, such as those related to climate change, aligns with the fiduciary responsibilities of institutional investors. Following the 2012 Kay Review on UK Equity Markets and Long-Term Decision Making, the UK government directed the Law Commission to investigate the duties of investment intermediaries. The Commission's findings indicated that trustees are permitted to account for ESG factors in their investment choices and are required to do so when these factors are financially material.

There is substantial evidence suggesting that this event may represent an exogenous shock to the demand for material climate commitment information from responsible investors. First, survey results in Krueger et al. (2020) and Bresnahan et al. (2020) indicate that fiduciary duties are one of the main reasons why institutional investors incorporate climate risks into their financial analysis. Therefore, by clarifying that the consideration of material ESG risks aligns with fiduciary duties, the 2013–2014 reform likely induced responsible investors to request detailed climate-related disclosures to support their financial analyses. A second example supports this interpretation: in their 2015 *Active Ownership Report*, Legal & General Investment explicitly mentioned fiduciary duty obligations as a reason for demanding greater disclosure from investee companies regarding their strategies for managing climate-related risks and opportunities.[10]

Using a two-way fixed-effects difference-in-differences framework, we test how UN PRI ownership affected firms' disclosure of material climate commitments before and after the UK Law Commission's clarification (2011–2015). We select this period following Gibson Brandon et al. (2022), who explain that it captures several years before and after the legal clarification and provides sufficient pre- and post-event observations for the difference-in-differences design.[11] In addition, restricting the sample to end in 2015 avoids potential confounding effects from subsequent policy and market developments, such as the 2015 Paris Agreement, that could confound the identification of the law's specific effects on responsible investment behaviour.[12] We thus estimate the following model:

$$\begin{aligned}\text{Specific Commitments}_{i,t} &= \beta_1 \,\text{High UK IO PRI}_{i,t} \cdot \text{Post Clarification}_t \\ &\quad + \beta_2 \,\text{High UK IO PRI}_{i,t} + X_{i,t} + \theta_i + \vartheta_t + \varepsilon_{i,t}\end{aligned} \tag{5.2}$$

where Specific Commitments$_{i,t}$ represents either the log of one plus the number of paragraphs in a firm annual report classified from ClimateBERT as specific commitments against (i) climate risks in general; (ii) climate transition risks or (iii) climate physical risks. Post Clarification$_t$ is a dummy variable taking the value of one 2013 onwards, which marks the years after the legal clarification, and zero in the years before. Note that the non-interacted

[10]For more information, see: `https://am.landg.com/en-uk/institutional/responsible-investing/active-ownership/`

[11]Following Gibson Brandon et al. (2022), we re-estimate the baseline DiD specification excluding 2013 (the year of the Law Commission's consultation paper) and define the years 2011–2012 as the pre-period and the years 2014–2015 as the post-period. Our results (untabulated) are qualitatively similar to this alternative specification.

[12]We further re-estimate the baseline DiD specification excluding 2015 to avoid any possible confounding effect arising from the Paris Agreement. Our results (untabulated) are qualitatively similar to this alternative specification.

effect of Post Clarification$_t$ is absorbed by time fixed effects. Treated firms are identified via the High UK IO PRI$_{i,t}$ indicator, which equals one if a firm's share of UK institutional investors who are UN PRI signatories is above the annual median. This specification identifies the average treatment effect on treated firms under the standard parallel-trends assumption that, absent the clarification, firms with high and low UK UN PRI ownership would have exhibited similar trends in the disclosure of material climate commitments. The coefficient of interest is therefore β_1, which captures how the disclosure of firms with high UK responsible ownership changes from before to after the legal clarification, relative to firms with low UK responsible ownership. All regressions include industry and year fixed effects. Standard errors are clustered at both the firm and year levels.

Table 5.4 provides the regression results. In column 1, we find that firms with high UK responsible ownership (High UK IO PRI) have a significantly higher levels of disclosure about specific commitments towards climate change risks after the legal clarification, compared to firms with lower UK responsible ownership. The magnitudes are also economically relevant. For instance, column 1 indicates after the legal clarification, disclosure of specific climate commitments increases by around 0.09 units more at firms with high UK responsible ownership compared to firms with low UK responsible ownership. This is a large effect considering the mean in the dependent variable of 1.16 during the estimation period. In line with the baseline results reported in Table 5.2, we find that the positive association between responsible ownership and disclosure is largely driven by material commitments towards climate transition risks (column 2), with no comparable effect for material commitments related to physical climate risks (column 3).

Finally, to assess the validity of the identification strategy, we conduct a placebo test using data from the pre-policy period 2006 to 2010, redefining the treatment window such that the placebo *Post Clarification* indicator equals one for years after 2007. Re-estimating the baseline specification over this sample yields no statistically significant effect of *High UK IO PRI * Post Clarification* on the disclosure of specific climate commitments. The absence of a pre-trend effect supports the parallel trends assumption and reinforces the interpretation that the observed post-2013 effects are driven by the fiduciary duty clarification rather than underlying differential trends between treated and control firms.

5.6 Consequences of Disclosure

In this section, we examine the capital market consequences of the change in corporate climate disclosure practices induced by responsible investors' demand. For this analysis, we focus on two equity-market dimensions: annual report filing returns and analyst forecast errors. The first dimension allows us to assess whether investor-driven climate disclosures convey new, relevant information to the market. The second dimension enables us to evaluate whether such investor-driven disclosures contain material information that is incorporated into the information set of equity research analysts. Together, these measures serve as proxies for the information content of investor-driven climate disclosures in annual reports.

As shown in Table 5.3, the effect of UN PRI ownership on the disclosure of material climate commitments is stronger when investee firms are inside the FTSE 350 index. Because such index membership is mechanically determined by market capitalization, and responsible ownership is predetermined relative to the release of the annual reports and analysts forecasts, this interaction provides a meaningful source of variation in disclosure that is unlikely to reflect differences in unobservable firm-level characteristics. Therefore, in the next two subsections, we rely on such empirical strategy to exploit variation in disclosure that potentially arises from *external* investor pressure, rather than from internal firm characteristics, allowing us to identify the causal impact of these information releases on equity market outcomes.

5.6.1 Equity market reactions to corporate disclosure

In our first capital market test, we examine whether responsible investors' demand for disclosure of material climate commitments improves the information content of annual reports. We test this by analysing the absolute cumulative abnormal return over the [-1, +1] period around annual report releases. According to Hypothesis 3.A, if UN PRI-investors induced disclosures of material climate commitments contain new information, then we would expect investors to react to the releases of such disclosures.

Table 5.5 reports the second stage results from instrumental variable regressions examining whether disclosure of specific climate-related commitments improves the informativeness of annual reports. Column (1) shows that a one-unit increase in the instrumented climate disclosure variable leads to an increase in the magnitude of abnormal stock returns around annual report releases by approximately 1.31 percentage points. Results are not only statistically significant but also economically meaningful. Given that the mean absolute CAR in the sample is 3.7% (see Table 5.1), this effect corresponds to approximately 36% of the average market reaction.

Consistent with the first part of the analysis, where we show that responsible investors selectively induce firms to disclose specific transition-related commitments, we find that only this subset of disclosures increase the information content of an annual report. Specifically, column (2) isolates disclosures related to specific commitments towards transition risk and yields a statistically significant effect comparable in magnitude to the total effect in column (1). On the other hand, column (3) examines disclosures related to specific commitments toward physical climate risks and reports a statistically insignificant coefficient. Moreover, while the first-stage F-statistics in the first two columns exceed conventional thresholds, the weak first-stage statistic in column (3) raises indicates potential weak instrument bias. Together, these results suggest that responsible investor engagement is effective in driving investee firms to disclose economically meaningful information that is incorporated into equity prices.

5.6.2 Analyst Forecast Accuracy

Prior literature showed that increases in corporate disclosure are reflected in analyst forecast accuracy (Bird and Karolyi, 2016). Given our instrumental variable framework, we can investigate the causal effect of changes in climate-related disclosure on analysts' forecasts accuracy. Furthermore, because the stock market results in the previous section might be subject to market microstructure concerns related to index inclusion, it is helpful to look at real outcomes, such as analyst forecast accuracy, which are directly related to information revelation. Without new material information, analysts would have no incentive to revise their forecasts.

Table 5.6 presents the second-stage results of a 2SLS estimation examining the impact of firm-level climate-related disclosures on analyst forecast accuracy. We report three main findings. First, consistent with Hypothesis 3.B, the results in Table 5.6 imply that UN PRI investors' demand for disclosure of material climate commitments improves the accuracy of analysts' EPS forecasts. Second, we observe that such effect is stronger, both statistically and economically, the longer the forecast horizon. Specifically, in column (1) we find that one-unit increase in the instrumented disclosure measure of specific climate-related commitments reduces the EPS forecast error for the current fiscal year by 2.37 percentage points. However, such result is statistically significant only at the 10% level. On the other hand, columns (2) and (3) show that a one-unit increase in the instrumented disclosure measure leads to a larger decline in forecast errors by 4.69% and 6.65% for the one-year-ahead and two-years-ahead horizons, respectively. Both effects are statistically significant at the 5% level. The effects are also economically relevant. For instance, given that the mean one-year-ahead forecast error in our sample is 5.3%, the 4.69% reduction reported in column (2) represents an 87.6% decline relative to the mean. The finding that UN PRI investors'-induced disclosure of specific climate commitments has a stronger effect on improving the accuracy of EPS forecast at longer forecast horizons is consistent with the notion that such disclosure contains *material* information about future earnings. This interpretation is consistent with the results in Ben-Amar et al. (2024), who found that corporate disclosure of climate change dynamics improves analysts' EPS accuracy (especially longer-period forecasting horizons) when such information is material.

Third, in Panel B, we find that the effect of the UN PRI investors-induced disclosure on the accuracy of EPS forecast is driven by specific climate transition risk commitments, not specific climate physical climate risk commitments (Panel C). Focusing on the coefficients significant at least at the 5% level in columns 2 and 3 of Panel B, they imply that one-unit increase in the instrumented disclosure measure of specific climate transition commitments reduces the EPS forecast error by 3.72% and 5.46% for the one-year-ahead and two-years-ahead horizons, respectively. These results are consistent with recent evidence that shows that analysts selectively incorporate transition risk–related climate disclosures into their reports (Chan, 2024). Our results complement the findings in Chan (2024) providing evidence on one possible channel why such information becomes available in the market. This suggests that the analysts' attention to climate disclosures is not random but facilitated by previous UN PRI investors' engagement with firms that shapes their ESG transparency in the market.

5.7 Conclusion

In this paper, we use a novel methodology based on ClimateBERT to quantify disclosure of material climate commitments in UK annual reports and examine UN-PRI institutional investors' preferences for such disclosures.

We report three main results. First, we find that, on average, an increase in stock ownership by UN PRI investors is positively correlated with a firms' decision to voluntarily disclose material climate commitments. Second, this relationship is primarily driven by disclosures related to climate transition risk, consistent with the notion that such commitments are more relevant to UN PRI investors for asset allocation purposes. Moreover, two exogenous shocks to UN PRI ownership support our baseline results, suggesting that the relationship we identify is likely causal. Finally, we show that UN PRI investors' demand for such information has a positive impact on the stock market reactions to annual report releases and accuracy of analysts' forecast, consistent with the notion that such disclosures contain new, material information.

Overall, our results have important policy implications for those equity markets where, at the time of writing, the disclosure of material climate commitments (and disclosure of climate change dynamics more in general) is still voluntary. In these markets, public policies that support the role of responsible investing (such as stewardship codes, or UN PRI-aligned investment frameworks), might lead to improved climate-related transparency across firms. As shown in our paper, this transparency would be particularly important given that the disclosed information is financially material, and would thus contribute to more informed decision-making by investors and more efficient capital markets.

5.8 Tables

Table 5.1: Summary Statistics. This table reports the summary statistics for the variables used in this study. Textual data was retrieved from Thomson Reuters DataStream and Companies House. Ownership Data was obtained from the Thomson Reuters Ownership database and the UN PRI dataset. Accounting and Sustainable Performance data were obtained from Worldscope and Refinitiv, respectively. Our sample includes all non-financial firms listed on the London Stock Exchange from 2006 to 2021. All continuous variables were winsorised at the 1% and 99% levels. Table A.5.2 provides detailed variable definitions.

Variable	N	Mean	SD	q25	Median	q75
Specific CC Commitments	16,957	1.3	1.2	0	1.1	2.2
Specific TR Commitments	16,957	0.92	1.1	0	0.69	1.6
Specific PR Commitments	16,957	0.081	0.28	0	0	0
IO PRI	16,957	13	15	0	6.1	21
IO non–PRI	16,957	27	20	9.9	25	42
LOG(TA)	16,957	11	2.4	9.6	11	13
DIV/NI	16,957	0.22	0.67	0	0	0.36
LEVERAGE	16,957	0.18	0.22	0.002	0.12	0.28
ROA	16,957	-0.1	0.43	-0.1	0.019	0.068
CAPEX	16,957	0.039	0.054	0.006	0.019	0.049
B/M	16,957	0.76	0.87	0.26	0.52	1
TCFD	16,957	0.006	0.078	0	0	0
CA100+	16,957	0.002	0.049	0	0	0
SBT	16,957	0.001	0.044	0	0	0
Opp/Risk	16,957	0.4	0.86	0	0	0.96
Climate Share	16,957	8.8	11	1.3	4.6	12
Emission Intensity	3,310	0.6	1.2	0.084	0.22	0.53
Environmental Score	4,699	42	25	23	41	61
abs(CAR[-1,+1])	5,089	3.7	5.6	0.91	2.1	4.3
FE(t)	9,610	0.044	0.11	0.004	0.011	0.035
FE(t+1)	8,088	0.053	0.095	0.009	0.022	0.059
FE(t+2)	6,146	0.064	0.098	0.012	0.030	0.072

Table 5.2: Responsible ownership and disclosure of specific climate-related commitments. This table examines whether responsible investor ownership affected the specificity of climate-related commitments in investee firms' annual reports from 2006 to 2021. In column (1) and (2), the dependent variable is the natural logarithm of 1 plus the number of firm-commitments against climate change risks classified as specific from ClimateBERT. In column (3) and (4), the dependent variable is the natural logarithm of 1 plus the number of firm-commitments against climate transition risks classified as specific from ClimateBERT. In column (5) and (6), the dependent variable is the natural logarithm of 1 plus the number of firm-commitments against climate physical risks classified as specific from ClimateBERT. IO UN PRI is the fraction of outstanding shares owned by institutional investors that were United Nations Principles for Responsible Investment signatories at the end of fiscal year. IO non-UN PRI is the fraction of outstanding shares owned by institutional investors that were not United Nations Principles for Responsible Investment signatories at the end of fiscal year. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.5.2 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	*Specific CC Commitments*		*Specific TR Commitments*		*Specific PR Commitments*	
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
IO PRI	0.008***	0.005***	0.008***	0.004***	0.000	-0.001
	(10.420)	(4.171)	(9.439)	(3.045)	(0.288)	(-0.939)
IO non–PRI	-0.001	0.002	-0.001	0.002	-0.001***	-0.001
	(-1.560)	(1.214)	(-1.008)	(1.396)	(-3.870)	(-1.148)
LOG(TA)	0.178***	0.150***	0.163***	0.149***	0.028***	0.029***
	(20.942)	(7.200)	(17.657)	(7.893)	(9.467)	(3.760)
DIV/NI	0.003	-0.003	0.001	-0.003	0.002	0.003
	(0.390)	(-0.230)	(0.092)	(-0.490)	(0.202)	(0.446)
B/M	-0.029**	0.020	-0.044***	-0.034	-0.008**	-0.020
	(-2.683)	(0.549)	(-4.363)	(-0.920)	(-2.280)	(-1.449)
ROA	-0.142***	-0.303*	-0.142***	-0.223	-0.012**	-0.046
	(-6.801)	(-1.914)	(-6.257)	(-1.580)	(-2.096)	(-0.358)
LEVERAGE	0.047	-0.042	0.046	-0.068	0.062	-0.078
	(1.237)	(-0.387)	(1.238)	(-0.679)	(1.505)	(1.142)
CAPEX	0.364**	1.429**	0.062	1.108*	0.097*	-0.002
	(2.405)	(2.620)	(0.412)	(2.063)	(2.115)	(-0.073)
TCFD	0.413***	0.240***	0.494***	0.248***	0.241***	0.229***
	(4.470)	(3.606)	(5.505)	(3.371)	(4.522)	(4.885)
SBT	0.279***	0.052	0.339***	0.152	-0.121***	-0.093***
	(4.373)	(0.701)	(4.518)	(0.315)	(-14.400)	(-8.228)
CA100+	0.185	-0.014	0.368*	0.109	-0.046	-0.242*
	(0.971)	(-0.086)	(1.847)	(0.673)	(-0.412)	(-2.080)
Climate Share	0.045***	0.048***	0.033***	0.043***	0.004***	0.006**
	(13.759)	(9.155)	(12.123)	(8.981)	(5.124)	(1.993)
Opp/Risk	0.460***	0.471***	0.365***	0.434***	0.012**	0.028*
	(27.607)	(18.841)	(24.305)	(22.543)	(2.429)	(2.016)
Resid.(Emission Intensity)		0.013		0.021		-0.018
		(0.476)		(0.911)		(-1.233)
Resid.(Environmental Score)		-0.025		-0.031		-0.008
		(-1.190)		(-1.422)		(-0.934)
Num.Obs.	16,957	3,307	16,957	3,307	16,957	3,307
R2 Adj.	0.719	0.595	0.655	0.541	0.157	0.195
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 5.3: Responsible ownership and disclosure of specific climate-related commitments: IV regressions. This table reports IV regression estimates of disclosure of specific climate commitments on responsible ownership and control variables. Panel A shows the first-stage regression results. Panel B, where IO PRI is instrumented with the FTSE 350 index, a dummy variable equal to one if the firm is a member of the FTSE350 index, and zero otherwise, shows the second-stage regression results. In Panel B, column (1) presents the second-stage results with the natural logarithm of one plus the number of firm-commitments against climate change risks classified as specific from ClimateBERT as the dependent variable. Column (3) presents the second-stage results with the natural logarithm of one plus the number of firm-commitments against climate transition risks classified as specific from ClimateBERT as the dependent variable. Column (5) presents the second-stage results with the natural logarithm of one plus the number of firm-commitments against climate physical risks classified as specific from ClimateBERT as the dependent variable. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.5.2 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: First stage Regression	
Dependent Variable:	*IO PRI*
Specification:	(1)
FTSE 350 (lag)	4.381***
	(6.947)
F statistic	50
Num. Obs.	16,303
R2 Adj.	0.503
Firm Controls	YES
Industry FE	YES
Year FE	YES

Panel B: Second stage Regression			
Dependent Variable:	*Specific CC Commitments*	*Specific TR Commitments*	*Specific PR Commitments*
Specification:	(1)	(3)	(5)
$\widehat{IO\ PRI}$	0.053***	0.056***	-0.002
	(5.394)	(6.391)	(-0.507)
Num. Obs.	16,303	16,303	16,303
R2 Adj.	0.569	0.429	0.153
Firm Controls	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES

Table 5.4: Specificity in the disclosure of climate-related commitments and responsible institutional investors: Effects of the UK 2013–2014 fiduciary duty law. This table reports the regression results of whether the UK 2013–2014 fiduciary duty law resulted in UK-domiciled UN PRI signatories increasing the specificity in the disclosure of climate-related commitments of their investee firms relative to uncommitted UK institutional investors. We use the following key independent variables: *Post Clarification* equals one for the years of 2013 and afterward, and zero otherwise; *HIGH UK IO UN PRI* is a dummy taking the value of one if the fraction of outstanding shares owned by UK institutional investors that were United Nations Principles for Responsible Investment signatories at the end of fiscal year is above the median of a given year. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.5.2 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	*Specific CC Commitments*	*Specific TR Commitments*	*Specific PR Commitments*
Specification:	(1)	(3)	(5)
*High UK IO PRI * Post Clarification*	0.089***	0.083**	0.004
	(3.039)	(2.101)	(0.309)
High UK IO PRI	-0.003	0.019	-0.022
	(-0.071)	(0.433)	(-1.732)
LOG(TA)	0.191***	0.177***	0.028***
	(19.445)	(16.513)	(7.993)
DIV/NI	0.024***	0.012	0.009
	(2.672)	(1.475)	(1.855)
B/M	-0.049***	-0.060***	-0.013***
	(-3.966)	(-4.713)	(-3.009)
ROA	-0.149***	-0.132***	-0.005
	(-6.322)	(-5.936)	(-0.589)
LEVERAGE	0.036	0.033	0.057
	(0.564)	(0.516)	(1.457)
CAPEX	0.647***	0.135	0.122
	(2.656)	(0.597)	(1.634)
Climate Share	0.045***	0.032***	0.004***
	(8.505)	(7.948)	(5.265)
Opp/Risk	0.481***	0.376***	0.024***
	(17.313)	(15.135)	(4.039)
Num. Obs.	5,288	5,288	5,288
R2 Adj.	0.684	0.606	0.187
Industry FE	YES	YES	YES
Year FE	YES	YES	YES

Table 5.5: Responsible ownership and the information content of specific climate-related commitments in UK annual reports. This table reports the results of the second stage of a two-stage least squares (2SLS) regression, where the dependent variable is the three days absolute cumulative abnormal return around the release of a firm annual report. The key independent variable is the instrumented natural logarithm of one plus the number of specific firm commitments classified by ClimateBERT against: climate change risks in general (column 1); climate transition risks (column 2); or climate physical risks (column 3). In all specifications, the key independent variable is instrumented using the interaction between responsible institutional ownership and FTSE 350 index membership. All continuous variables are winsorized at the 1st and 99th percentiles. t-statistics are reported in parentheses, and standard errors are double clustered at the firm and year levels. Variable definitions are provided in Table A.5.2. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:		*abs(CAR[-1,+1])*	
Specification:	(1)	(2)	(3)
$\widehat{\textit{Specific CC Commitments}}$	1.344**		
	(2.143)		
$\widehat{\textit{Specific TR Commitments}}$		1.283**	
		(2.298)	
$\widehat{\textit{Specific PR Commitments}}$			-12.662
			(-1.500)
IO non–PRI	-0.003	-0.003	-0.011
	(-0.708)	(-0.768)	(-1.443)
LOG(TA)	-0.573***	-0.542***	0.134
	(-4.174)	(-4.162)	(1.067)
DIV/NI	-0.056	-0.049	-0.043
	(-1.430)	(-1.094)	(-0.938)
B/M	0.451*	0.482*	0.408
	(2.001)	(2.107)	(2.087)
ROA	-1.767***	-1.764***	-2.303***
	(-2.979)	(-3.041)	(-3.532)
LEVERAGE	0.557	0.589*	1.043**
	(1.572)	(1.884)	(2.686)
CAPEX	1.179	1.264	2.409*
	(1.571)	(1.868)	(1.948)
TCFD	0.900	1.233*	2.658*
	(1.025)	(1.640)	(1.902)
SBT	-1.380***	-1.482***	-2.760**
	(-1.896)	(-2.029)	(-2.657)
CA100+	-1.420***	-1.386***	-2.180*
	(-3.469)	(-3.500)	(-2.370)
Climate Share	-0.117	-0.123	-0.087
	(-0.923)	(-1.346)	(-1.257)
Opp/Risk	-0.738**	-0.588**	0.047
	(-2.248)	(-2.339)	(0.303)
F statistic (first stage)	30.7	31.2	2.78
Num. Obs.	5,809	5,809	5,809
R2 Adj.	0.440	0.485	0.395
Industry FE	YES	YES	YES
Year FE	YES	YES	YES

Table 5.6: Responsible ownership and the information content of specific climate commitments in annual reports for equity analysts. This table reports the results of the second stage of a two-stage least squares regression, where the dependent variable is EPS forecast error for three different forecast horizons: current fiscal year (column 1), one-year-ahead (column 2), and two-years-ahead (column 3). The EPS forecast error is measured as the average monthly value of the absolute difference between analyst mean estimates and actual earnings, then scaled by stock price at the beginning of the fiscal year. The key independent variable is the instrumented natural logarithm of one plus the number of specific firm commitments classified by *ClimateBERT* against: climate change risks in general (Panel A); climate transition risks (Panel B); or climate physical risks (Panel C). In all specifications, the key independent variable is instrumented using the interaction between lagged responsible institutional ownership and lagged FTSE 350 index membership. All continuous variables are winsorized at the 1st and 99th percentiles. t-statistics are reported in parentheses, and standard errors are double clustered at the firm and year levels. Variable definitions are provided in Table A.5.2. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Specific Climate Change Risk Commitments and Forecast Error

Dependent Variable:	$FE(t)$	$FE(t+1)$	$FE(t+2)$
Specification:	(1)	(2)	(3)
$\widehat{\textit{Specific CC Commitments}}$ (lag)	-2.370*	-4.686**	-6.648**
	(1.849)	(2.314)	(2.268)
F statistic (first stage)	32.3	22.6	15.5
Control Variables	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Num.Obs.	9,610	8,088	6,146
R2 Adj.	0.166	0.094	0.030

Panel B. Specific Climate Transition Risk Commitments and Forecast Error

Dependent Variable:	$FE(t)$	$FE(t+1)$	$FE(t+2)$
Specification:	(1)	(2)	(3)
$\widehat{\textit{Specific TR Commitments}}$ (lag)	-1.783*	-3.720**	-5.462**
	(1.708)	(2.484)	(2.275)
F statistic (first stage)	42.1	32.3	17.9
Control Variables	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Num.Obs.	9,610	8,088	6,146
R2 Adj.	0.179	0.153	0.077

Panel C. Specific Climate Physical Risk Commitments and Forecast Error

Dependent Variable:	$FE(t)$	$FE(t+1)$	$FE(t+2)$
Specification:	(1)	(2)	(3)
$\widehat{\textit{Specific PR Commitments}}$ (lag)	-2.969	8.646	19.628
	(0.341)	(0.855)	(1.151)
F statistic (first stage)	2.2	2.77	1.58
Control Variables	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Num.Obs.	9,610	8,088	6,146
R2 Adj.	0.182	0.156	0.210

5.9 Appendix

5.9.1 Manual Validation of ClimateBERT Classifiers

To address the concern regarding potential misclassification by the ClimateBERT classifiers, we conducted a manual audit to assess the reliability of the ClimateBERT algorithm within our sample. The purpose of this validation was to verify the quality and consistency of the automated classifications and to evaluate whether the model's predictions align with human judgement.

Specifically, a manual validation test was carried out using 150 paragraphs randomly selected from 150 unique annual reports within the corpus of annual reports in our sample. Of these, 100 paragraphs contained at least one term from the climate-related lexicon used in Bingler et al. (2024).[13] The remaining 50 paragraphs did not contain any of these terms and were included to provide a neutral baseline. This balanced sampling design allowed for a more comprehensive evaluation of both positive and negative classification performance.

Each paragraph was manually labelled according to the same four classification tasks performed by ClimateBERT:

- **Climate-related**: whether the paragraph discusses climate issues;
- **Climate-risk type**: identification of the type of climate risk (physical or transition risk);

[13] The climate-related terms used for training sample extraction are: air quality, bushfire, carbon, CH4, climate, climate-related, CO2, coal, decarbonization, decarbonisation, deforestation, drought, emission, energy consumption, energy efficiency, energy efficient, energy transition, environmental, ESG, footprint, fossil, GHG, global warming, greenhouse, heat wave, hurricane, land use, litigation risk, low-carbon, methane, N2O, natural hazard, nitrous oxide, O3, ozone, Paris Agreement, physical risk, renewable, rural fire, sea level, social responsibility, solar energy, sustainable, sustainability, TCFD, temperature rise, transition risk, tropical cyclone, tropical storm, typhoon, weather, wildfire, wildland fire, and wind energy.

- **Commitment & Actions**: whether the text refers to commitments, targets, or actions taken;
- **Specificity**: the degree of detail in the paragraph with respect to the climate-related commitment.

We report the results in Table A.5.1. The results confirm the robustness of the ClimateBERT classifiers. The *Climate-related* and *Climate-risk type* tasks achieved high and balanced performance across all metrics (around 0.9 or higher), indicating a reliable distinction between relevant and non-relevant climate-related text segments. The *Commitment & Actions* and *Specificity* classifiers produced slightly lower scores (around 0.7), which is expected given the more complex and context-dependent nature of these classifications. Nevertheless, these values still reflect acceptable performance for exploratory and large-scale text analysis and are consistent with the performance metrics reported in Bingler et al. (2024). Overall, this validation test confirms that the ClimateBERT classifiers perform with sufficient accuracy for the purposes of this research, and that the risk of systematic misclassification remains limited.

Table A.5.1: Validation results of the ClimateBERT classifiers based on manual auditing. The table reports the values for accuracy, precision, recall, and F1 scores for each classifier. A manual validation test was conducted using 150 paragraphs randomly selected from 150 unique annual reports within the corpus of annual reports in our sample. Of these, 100 paragraphs contained at least one term from the climate-related lexicon used in Bingler et al. (2024) to assess ClimateBERT's performance, while the remaining 50 paragraphs did not contain any of these terms and served as a neutral baseline.

Task	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Climate-related	0.95	0.93	0.94	0.94
Climate-risk type	0.89	0.91	0.88	0.89
Commitment & Actions	0.74	0.72	0.75	0.73
Specificity	0.72	0.74	0.70	0.72

5.9.2 Additional Information about the Responsible Ownership Data

In this appendix, we explain the steps to match the UN PRI signatory list to the institutional equity holdings data from Thomson Reuters Ownership. As a first step, we standardise the names of institutions found in the Thomson Reuters Ownership and UN PRI datasets by removing punctuation, accents, special characters, and other non-alphanumeric elements. We then apply a fuzzy matching algorithm to compare the two sets of institution names and identify the closest matches based on string similarity.

In a second step, we manually check the validity of the initial output of the name-matching algorithm by controlling for the country location of the signatory' headquarter, the asset class composition of its holdings as reported to PRI, and the website URLs reported to PRI and from Thomson Reuters Ownership.

In the third step, we deal with double matches that appear between the UN PRI and the Thomson Reuters Ownership databases. This can happen when both the parent and the entity sign the PRI independently. To retain unique cases, we follow the strategy proposed in Gibson Brandon et al. (2022). First, we give priority to entity over parent matches. Second, whenever a parent signed but the entities did not, we again follow Gibson Brandon et al. (2022) and assume that the entities inherit the PRI status, but not vice versa.

5.9.3 Additional Tables

Table A.5.2: Variable Definitions. This table describes the variables used in our analyses and their respective sources. Data sources are: CA100+ = CA100+ database; CH = Companies House; DS = Thomson Reuters DataStream; IBES = Institutional Brokers' Estimate System; R = Refinitiv; SBT = SBT database; TCFD = TCFD database; TRE = Thomson Reuters Eikon; TRO = Thomson Reuters Ownership; UN-PRI = UN PRI database; W = Worldscope.

Variable	Definition and Sources
Specific CC Commitments	Natural logarithm of one plus the number of climate-related paragraphs in an annual report classified as both 'commitment' and 'specific' by ClimateBERT. (Source: CH, TRE)
Specific TR Commitments	Natural logarithm of one plus the number of climate-related paragraphs in an annual report classified as both 'transition climate risk related,' 'commitment' and 'specific' by ClimateBERT. (Source: CH, TRE)
Specific PR Commitments	Natural logarithm of one plus the number of climate-related paragraphs in an annual report classified as both 'physical climate risk related,' 'commitment' and 'specific' by ClimateBERT. (Source: CH, TRE)
IO PRI	Fraction of outstanding firm shares owned by institutional investors that are UN PRI signatories in a year. (Source: TRO, UN-PRI)
IO non–PRI	Fraction of outstanding firm shares owned by institutional investors that are not UN PRI signatories in a year. (Source: TRO, UN-PRI)
LOG(TA)	Natural logarithm of firm's total assets. (Source: W)
DIV/NI	Dividends at the end of the year, divided by net income/loss at the end of the year. (Source: W)

Variable	Definition and Sources
LEVERAGE	Sum of the book value of long-term debt and the book value of current liabilities at the end of the year, divided by total assets at the end of the year. (Source: W)
ROA	Net income, divided by total assets of the same year. (Source: W)
CPX/TA	Capital Expenditures, divided by total assets of the same year. (Source: W)
B/M	Book value of shareholder equity, divided by the market capitalisation at the end of the fiscal year. (Source: W)
TCFD	Dummy variable taking the value of one if a firm reports following the TCFD guidelines in a given year, zero otherwise. (Source: TCFD)
CA100+	Dummy variable taking the value of one if a firm is into the CA100+ database in a certain year, zero otherwise. (Source: CA100+)
SBT	Dummy variable taking the value of one if a firm is into the SBT database in a certain year, zero otherwise. (Source: SBT)
Opp/Risk	Logarithm of the number of climate-related paragraphs classified as opportunity plus one divided by the number of climate-related paragraphs classified as risk plus one. (Source: CH, TRE)
Climate Share	Number of climate-related paragraphs in an annual report classified as 'climate' related by ClimateBERT. (Source: CH, TRE)
Environmental Score	Industry-adjusted Refinitiv's Environment Pillar Score. (Source: R)
Emission Intensity	Total emissions (scope 1 + scope 2), divided by property, plant and equipment of the same year. (Source: R, W)

Variable	**Definition and Sources**
abs(CAR[-1,+1])	Absolute cumulative abnormal return over a three-day window around the filing date of an annual report. (Source: DS)
FE(t)	A firm's analyst forecast error at year t for current fiscal year t. The analyst forecast error is measured as the average monthly value of the absolute difference between analyst mean estimates and actual earnings, then scaled by stock price at the beginning of the year. (I/B/E/S summary). (Source: DS, IBES)
FE(t+1)	A firm's analyst forecast error at year t for the fiscal year in t+1. The analyst forecast error is measured as the average monthly value of the absolute difference between analyst mean estimates and actual earnings, then scaled by stock price at the beginning of the year. (Source: DS, IBES)
FE(t+2)	A firm's analyst forecast error at year t for the fiscal year in t+2. The analyst forecast error is measured as the average monthly value of the absolute difference between analyst mean estimates and actual earnings, then scaled by stock price at the beginning of the year. (Source: DS, IBES)

Table A.5.3: Responsible Ownership and Sustainability Performances. This table examines whether responsible investor ownership affected the emission intensity and environmental scores of their investee firms from 2006 to 2021. In column (1), the dependent variable is the sum of scope 1 and scope 2 emissions scaled by fixed assets. In column (2), the dependent variable is the environmental score provided by Refinitiv Eikon. IO UN PRI (lag) is the fraction of outstanding shares owned by institutional investors that were United Nations Principles for Responsible Investment signatories at the end of the previous fiscal year. IO non-UN PRI (lag) is the fraction of outstanding shares owned by institutional investors that were not United Nations Principles for Responsible Investment signatories at the end of the previous fiscal year. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.5.2 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	*Emission Intensity*	*Environmental Score*
Specification	(1)	(2)
IO UN PRI (lag)	-0.009**	0.187***
	(-2.300)	(4.486)
IO non–UN PRI (lag)	0.001	0.118***
	(0.315)	(3.398)
LOG(TA) (lag)	-0.033	9.677***
	(-0.963)	(17.417)
DIV/NI (lag)	0.038	0.029
	(1.628)	(0.181)
B/M (lag)	-0.012	-2.414**
	(-0.561)	(-2.227)
ROA (lag)	0.017	7.184
	(0.516)	(1.804)
LEVERAGE (lag)	-0.062	-0.203
	(-0.272)	(-0.842)
CAPEX (lag)	-2.783	-2.074
	(-1.463)	(-1.057)
TCFD (lag)	0.106	0.243
	(0.728)	(1.008)
SBT (lag)	0.297**	0.715
	(2.147)	(1.838)
CA100+ (lag)	-0.564***	-0.754*
	(-2.783)	(-1.842)
Climate Share (lag)	0.032***	0.287***
	(3.112)	(3.107)
Opp/Risk (lag)	-0.041	0.113***
	(-1.420)	(3.147)
Num.Obs.	3,274	4,618
R2 Adj.	0.138	0.490
Industry FE	YES	YES
Year FE	YES	YES

Table A.5.4: Quasi-Natural Experiment Based on FTSE 350 Index Additions. This table presents the estimation results of institutional ownership and firm-level disclosure effects around stock additions to the FTSE 350 Index. The sample includes index additions during the 2006–2021 period. The index additions occur between year –1 and year 0. Treated firms are those that are added to the FTSE 350, while control firms are the nearest-neighbour firms that best match treated firms in year –1 on multiple variables (Year and *IO UN PRI*). Panel A reports the comparison of sample means between treated and control firms. Panel B reports the estimation results of the difference-in-differences analysis. The dependent variable is UN PRI institutional ownership in column (1), traditional institutional ownership in column (2), the natural logarithm of one plus the number of firm commitments to addressing climate change risks classified as specific by ClimateBERT in column (3), the natural logarithm of one plus the number of firm commitments to addressing climate transition risks classified as specific by ClimateBERT in column (4), and the natural logarithm of one plus the number of firm commitments to addressing climate physical risks classified as specific by ClimateBERT in column (5). *Treated* is coded as 1 if a firm is in the treated firm sample, and 0 otherwise. *Post* is coded as 1 if a year is after the index additions, and 0 otherwise. All continuous variables were winsorised at the 1% and 99% levels. t-statistics are reported in parentheses, and standard errors are double-clustered at the firm and year levels. Table A.5.2 defines all variables in detail. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Summary Statistics (Pre-Treatment)

	Treated Firms	**Control Firms**	**t-test**
IO UN PRI	18.7	19.9	1.471
IO non-UN PRI	36.5	37.1	0.762
Specific CC Commitments	1.51	1.49	1.488
Specific TR Commitments	1.52	1.48	1.354
Specific PR Commitments	0.16	0.18	1.535

Panel B: Difference-in-Differences Analysis

	(1) *IO UN PRI*	(2) *IO non-UN PRI*	(3) *Specific CC Commitments*	(4) *Specific TR Commitments*	(5) *Specific PR Commitments*
Treated × *Post*	5.52***	0.001	0.222**	0.232**	0.019
	(3.681)	(0.221)	(1.998)	(2.198)	(0.371)
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	795	795	795	795	795
Adj. R^2	0.755	0.669	0.675	0.673	0.359

Chapter 6

Conclusions and Further Research

6.1 Concluding Remarks

This dissertation contributes to the literature on how climate change disclosure is priced, demanded and employed in capital markets, specifically focusing on UK firms listed on the London Stock Exchange. Across three empirical chapters, I provide new evidence on: (1) how investors price physical climate risk disclosure when a firm is impacted by a natural disaster; (2) whether investors reward firms impacted by a natural disaster if they report about adaptation strategies against physical climate risks; and (3) whether responsible investors influence the decision of their investee firms to voluntarily disclose material climate commitments and the market implications of these types of investors' engagements.

The first empirical chapter (Chapter 3) investigates the effect of physical climate risk disclosures on firm value around exogenous natural disaster events. Using a text-based measure to capture physical climate risk disclosure, I show that disclosing companies affected by natural disasters experience smaller declines in share prices than similarly impacted firms that withhold such information. Further analysis, grounded in asset pricing theory, suggests that the mitigating effect of disclosure on firm value operates through a reduction in investor ambiguity, as evidenced by higher stock liquidity among affected disclosing firms in the aftermath of natural disasters. Overall, these results align with the predictions of Guay and Verrecchia (2018), whose theoretical framework suggests that the disclosure of adverse information, such as exposure to physical climate risks, reduces investor uncertainty and stabilises firm valuations during periods of heightened information asymmetry.

The second empirical chapter (Chapter 4) builds on the approach proposed in Chapter 3 and develops two novel textual measures based on a dictionary of climate adaptation verbs. These measures allows to distinguish between firms that communicate their strategies to address physical climate risks and those that limit their disclosures to physical risk exposure. Investigating how investors value these different disclosure practices during climate-related shocks, I find that while transparency about risk exposure helps mitigate valuation losses, firms that also disclose adaptation strategies do not experience the same benefits. Supporting the view that only disclosure of physical climate risk exposure reduces investor uncertainty, I observe increased stock liquidity after natural disasters only for firms that refrain from disclosing climate adaptation strategies. These results are in line with recent interview evidence from UK corporate managers, suggesting that firms may have historically avoided detailed climate adaptation disclosures to prevent potential costs linked to investor misinterpretation of such information (Tang, 2022).

The final empirical chapter (Chapter 5) examines the role of institutional investors committed to the United Nations Principles for Responsible Investment (UN PRI) in influencing the voluntary disclosure of material climate commitments by UK firms. Using ClimateBERT-based classifications, I find that UN PRI investors encourage investee firms to disclose material climate commitments, particularly those related to transition risks rather than physical climate risks. Further tests based on exogenous FTSE 350 index inclusions and a difference-in-differences design exploiting the 2013–2014 UK fiduciary duty reform provide evidence that this relationship is likely causal. Moreover, I show that disclosures induced by UN PRI investors carry information content, as they are associated with positive abnormal returns around annual report filings and improved analyst forecast accuracy. Overall, these results suggest that UN PRI investors not only act as active stewards prompting firms to disclose material climate commitments, but also contribute to improved price discovery and informational efficiency in capital markets.

6.2 Further Research

This dissertation opens several promising avenues for future research. First, building on the analysis in Chapter 3, future work could benefit from more granular data on ownership structures within business groups and improved subsidiary-level accounting information. The current lack of such data limits the ability to assess how group-wide and international exposures to natural disasters affect the relationship between physical climate risk disclosure and firm valuation. More specifically, incorporating time-varying accounting data at the subsidiary level, and capturing multinational exposure patterns, would allow researchers to evaluate whether the positive relationship between firm value and disclosure around natural disaster events also extends to physical risk exposure at the international, and not only the domestic, level.

Second, extending the findings from Chapter 4, further research could investigate whether markets differentiate between various types of climate adaptation strategies, such as "soft" measures (e.g. risk planning, training, and internal guidelines) versus "hard" investments (e.g. infrastructure upgrades or technological systems). Moreover, future studies could explore the pricing of adaptation not only at the firm level but also along the supply chain. An open question, for instance, is whether investors perceive and price cascading climate adaptation strategies. Investors may, for example, price a firm's exposure to physical risk differently if its suppliers have climate adaptation mechanisms in place. This would help clarify the extent to which investors consider interconnections in climate adaptation strategies within their valuation processes.

Third, the results of Chapter 5 raise important questions about the motivations and mechanisms underlying responsible investors' preferences for climate change disclosure. One area for future inquiry is the examination of why UN PRI investors appear more inclined to demand voluntary disclosure of climate transition-related commitments rather than those concerning physical climate risks. This asymmetry may indicate more than a difference in material relevance; it could reflect a systematic "transition bias" within responsible investment practices. Such bias may stem from multiple sources, including the short-term horizons that dominate market decision-making, regulatory frameworks that primarily emphasise transition risk management (for example, through emissions targets or net-zero commitments), and the greater availability and comparability of transition-related data relative to physical risk metrics (Hain et al., 2022). Therefore, the emphasis on transition risks at the expense of physical climate risks raises broader questions about whether responsible investors (and financial markets more in general) are internalising long-term adaptation challenges (Goldstein et al., 2019). Moreover, while these findings infer investor preferences from observable market reactions and ownership patterns, they do not capture direct evidence of engagement practices. Therefore, further research could investigate the channels through which responsible investors exert influence (i.e. through active engagement ("voice") or the threat of divestment ("exit")) using qualitative or institutional data (such as interviews, surveys, or shareholder meeting records). This would provide a more clear understanding of how institutional pressure on climate disclosure is operationalised in practice.

Finally, while this dissertation focuses on a developed equity market such as the London Stock Exchange, this focus improves internal consistency in terms of regulatory environment, disclosure standards, and investor composition, but necessarily limits the external validity of our findings. Climate disclosure practices, investor pressures, and regulatory environments differ substantially across jurisdictions, so the patterns observed in the UK may not generalise directly to other contexts. Extending the analysis to other asset classes and geographies therefore represents an important next step. Climate risk disclosure has implications not only for equity investors but also for debt markets, minority shareholders, and broader societal resilience. Comparative analyses across bond and credit markets could reveal whether transparency around climate risk and adaptation disclosures affects borrowing costs, access to finance, and the resilience of financially constrained firms. Similarly, extending research to emerging and developing economies could shed light on how institutional structures, regulatory capacity, and exposure to climate risks shape both the effectiveness and quality of disclosure practices. Importantly, analyses focusing on developing countries should integrate perspectives from climate justice and distributional economics to determine whether disclosure regimes contribute to narrowing or widening inequalities in the face of climate change (Foerster, 2019). Taken together, these avenues offer rich potential for advancing our understanding of the economic consequences and transmission channels of climate-related disclosures in financial markets.

Bibliography

Addoum, J. M., Ng, D. T., and Ortiz-Bobea, A. (2020). Temperature shocks and establishment sales. *The Review of Financial Studies*, 33(3):1331–1366.

Addoum, J. M., Ng, D. T., and Ortiz-Bobea, A. (2023). Temperature shocks and industry earnings news. *Journal of Financial Economics*, 150(1):1–45.

Admati, A. R. and Pfleiderer, P. (2000). Forcing firms to talk: Financial disclosure regulation and externalities. *The Review of Financial Studies*, 13(3):479–519.

Akey, P. and Appel, I. (2019). Environmental externalities of activism. *Available at SSRN 3508808.*

Akey, P. and Appel, I. (2021). The limits of limited liability: Evidence from industrial pollution. *The Journal of Finance*, 76(1):5–55.

Alok, S., Kumar, N., and Wermers, R. (2020). Do fund managers misestimate climatic disaster risk. *The Review of Financial Studies*, 33(3):1146–1183.

Amel-Zadeh, A. (2021). The financial materiality of climate change: Evidence from a global survey. *Available at SSRN 3295184.*

Aminadav, G. and Papaioannou, E. (2020). Corporate control around the world. *The Journal of Finance*, 75(3):1191–1246.

Andersson, M., Bolton, P., and Samama, F. (2016). Hedging climate risk. *Financial Analysts Journal*, 72(3):13–32.

Anton, S. G. (2021). The impact of temperature increase on firm profitability. Empirical evidence from the European energy and gas sectors. *Applied Energy*, 295:117051.

Anttila-Hughes, J. (2016). Financial market response to extreme events indicating climatic change. *The European Physical Journal Special Topics*, 225(3):527–538.

Ardia, D., Bluteau, K., Boudt, K., and Inghelbrecht, K. (2023). Climate change concerns and the performance of green vs. brown stocks. *Management Science*, 69(12):7607–7632.

Atanasova, C. and Schwartz, E. S. (2019). Stranded fossil fuel reserves and firm value. Technical report.

Avramov, D., Cheng, S., Lioui, A., and Tarelli, A. (2022). Sustainable investing with esg rating uncertainty. *Journal of Financial Economics*, 145(2):642–664.

Azar, J., Duro, M., Kadach, I., and Ormazabal, G. (2021). The big three and corporate carbon emissions around the world. *Journal of Financial Economics*.

Baker, A. C., Larcker, D. F., and Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, 144(2):370–395.

Baldauf, M., Garlappi, L., and Yannelis, C. (2020). Does climate change affect real estate prices? Only if you believe in it. *The Review of Financial Studies*, 33(3):1256–1295.

Balvers, R., Du, D., and Zhao, X. (2017). Temperature shocks and the cost of equity capital: Implications for climate change perceptions. *Journal of Banking & Finance*, 77:18–34.

Banerjee, S., Davis, J., and Gondhi, N. (2018). When transparency improves, must prices reflect fundamentals better? *The Review of Financial Studies*, 31(6):2377–2414.

Bansal, R., Kiku, D., and Ochoa, M. (2016). Price of long-run temperature shifts in capital markets. *National Bureau of Economic Research*.

Bansal, R., Kiku, D., and Ochoa, M. (2019). Climate change risk. *National Bureau of Economic Research*.

Barahona, R., Driessen, J., and Frehen, R. (2021). Can unpredictable risk exposure be priced? *Journal of Financial Economics*.

Barnett, M. (2023). Climate change and uncertainty: An asset pricing perspective. *Management Science*, 69(12):7562–7584.

Barnett, M., Brock, W., and Hansen, L. P. (2020). Pricing uncertainty induced by climate change. *The Review of Financial Studies*, 33(3):1024–1066.

Bartram, S. M., Hou, K., and Kim, S. (2021). Real effects of climate policy: Financial constraints and spillovers. *Journal of Financial Economics*.

Bassi, A., Colacito, R., and Fulghieri, P. (2013). 'O sole mio: An experimental analysis of weather and risk attitudes in financial decisions. *The Review of Financial Studies*, 26(7):1824–1852.

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., and Visentin, G. (2017). A climate stress-test of the financial system. *Nature Climate Change*, 7(4):283–288.

Ben-Amar, W., Herrera, D. C., and Martinez, I. (2024). Do climate risk disclosures matter to financial analysts? *Journal of Business Finance & Accounting*, 51(7-8):2153–2180.

Ben-David, I., Jang, Y., Kleimeier, S., and Viehs, M. (2018). Exporting pollution: Where do multinational firms emit co2? *Economic Policy*.

Benz, L., Jacob, A., Paulus, S., and Wilkens, M. (2020). Herds on green meadows: The decarbonization of institutional portfolios. *Journal of Asset Management*, 21(1):13–31.

Berg, F., Kölbel, J. F., and Rigobon, R. (2022). Aggregate confusion: The divergence of esg ratings. *Review of Finance*, 26(6):1315–1344.

Berkman, H., Jona, J., and Soderstrom, N. (2024). Firm-specific climate risk and market valuation. *Accounting, Organizations and Society*, 112:101547.

Bernstein, A., Gustafson, M. T., and Lewis, R. (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics*, 134(2):253–272.

Bingler, J. A., Kraus, M., Leippold, M., and Webersinke, N. (2024). How cheap talk in climate disclosures relates to climate initiatives, corporate emissions, and reputation risk. *Journal of Banking & Finance*, 164:107191.

Bird, A. and Karolyi, S. A. (2016). Do institutional investors demand public disclosure? *The Review of Financial Studies*, 29(12):3245–3277.

Black, D. E., Isidro, H., and Marques, A. C. (2024). Investor commitment to responsible investing and firm esg disclosure. *Available at SSRN 4205956*.

Blank, H., Davis, R., and Greene, S. (2019). Using alternative research data in real-world portfolios. *The Journal of Investing*, 28(4):95–103.

Bolton, P. and Kacperczyk, M. (2020). Carbon premium around the world. *Available at SSRN*.

Bolton, P. and Kacperczyk, M. (2021a). Do investors care about carbon risk? *Journal of Financial Economics*.

Bolton, P. and Kacperczyk, M. (2021b). Firm commitments. *Available at SSRN 3840813*.

Bond, P. and Zeng, Y. (2022). Silence is safest: Information disclosure when the audience's preferences are uncertain. *Journal of Financial Economics*, 145(1):178–193.

Boone, A. L. and White, J. T. (2015). The effect of institutional ownership on firm transparency and information production. *Journal of Financial Economics*, 117(3):508–533.

Bouchet, V., Dayan, H., and Contoux, C. (2021). Finance and climate science: worlds apart? *Journal of Risk Research*, pages 1–22.

Bourdeau-Brien, M. and Kryzanowski, L. (2017). The impact of natural disasters on the stock returns and volatilities of local firms. *The Quarterly Review of Economics and Finance*, 63:259–270.

Bourdeau-Brien, M. and Kryzanowski, L. (2020). Natural disasters and risk aversion. *Journal of Economic Behavior & Organization*, 177:818–835.

Bowen, A. and Rydge, J. (2011). Climate-change policy in the united kingdom.

Bresnahan, K., Frankenreiter, J., L'Helias, S., Hinricks, B., Hodzic, N., Nyarko, J., Pandya, S., and Talley, E. L. (2020). Global investor-director survey on climate risk management. *Available at SSRN 3722958*.

Busch, T., Johnson, M., Pioch, T., and Kopp, M. (2018). Consistency of corporate carbon emission data. *Hamburg. Retrieved September*, 29:2018.

Campbell, J. Y. and Shiller, R. J. (1988). Stock prices, earnings, and expected dividends. *The Journal of Finance*, 43(3):661–676.

Campbell, J. Y. and Vuolteenaho, T. (2004). Bad beta, good beta. *American Economic Review*, 94(5):1249–1275.

Campiglio, E., Dafermos, Y., Monnin, P., Ryan-Collins, J., Schotten, G., and Tanaka, M. (2018). Climate change challenges for central banks and financial regulators. *Nature Climate Change*, 8(6):462–468.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 52(1):57–82.

Carney, M. (2015). Breaking the tragedy of the horizon–climate change and financial stability. *Speech given at Lloyd's of London*, 29:220–230.

Ceccarelli, M., Ramelli, S., Wagner, A. F., et al. (2019). When investors call for climate responsibility, how do mutual funds respond? Technical report.

CFA (2020). Climate change analysis in the investment process. Technical report.

Chan, J. (2024). Analysts' perspectives on climate change: An examination of analyst reports. *Available at SSRN 4890118*.

Chava, S. (2014). Environmental externalities and cost of capital. *Management Science*, 60(9):2223–2247.

Cheema-Fox, A., LaPerla, B. R., Serafeim, G., Turkington, D., and Wang, H. (2021). Decarbonizing everything. *Financial Analysts Journal*, pages 1–16.

Choi, D., Gao, Z., and Jiang, W. (2020). Attention to global warming. *The Review of Financial Studies*, 33(3):1112–1145.

Chu, Y., Liu, A. Y., and Tian, X. (2020). Environmental risk and green innovation: Evidence from evacuation spills. *Available at SSRN 3740551*.

Chu, Y. and Zhao, D. (2019). Green hedge fund activists. *Available at SSRN 3499373*.

Chung, K. H. and Zhang, H. (2014). A simple approximation of intraday spreads using daily data. *Journal of Financial Markets*, 17:94–120.

Crawford, M. and Seidel, S. (2013). Weathering the storm: Building business resilience to climate change. *Center for Climate and Energy Solutions*, page 112.

Curtin, J., McInerney, C., Gallachóir, B. Ó., Hickey, C., Deane, P., and Deeney, P. (2019). Quantifying stranding risk for fossil fuel assets and implications for renewable energy investment: A review of the literature. *Renewable and Sustainable Energy Reviews*, 116:109402.

Dai, R., Duan, R., Liang, H., and Ng, L. (2021). Outsourcing climate change. *European Corporate Governance Institute–Finance Working Paper*, (723).

Dai, R., Liang, H., and Ng, L. (2020). Socially responsible corporate customers. *Journal of Financial Economics*.

Daniel, K. D., Litterman, R. B., and Wagner, G. (2016). Applying asset pricing theory to calibrate the price of climate risk. Technical report.

Davies, S. W. and Van Wesep, E. D. (2018). The unintended consequences of divestment. *Journal of Financial Economics*, 128(3):558–575.

De Haas, R., Martin, R., Muûls, M., and Schweiger, H. (2021). Managerial and financial barriers to the net-zero transition. *BOFIT Discussion Paper*.

Dell, M., Jones, B. F., and Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95.

Dessaint, O. and Matray, A. (2017). Do managers overreact to salient risks? Evidence from hurricane strikes. *Journal of Financial Economics*, 126(1):97–121.

Diamond, D. W. and Verrecchia, R. E. (1991). Disclosure, liquidity, and the cost of capital. *The Journal of Finance*, 46(4):1325–1359.

Diaz-Rainey, I., Gehricke, S. A., Roberts, H., and Zhang, R. (2021). Trump vs. Paris: The impact of climate policy on US listed oil and gas firm returns and volatility. *International Review of Financial Analysis*, 76:101746.

Diaz-Rainey, I., Robertson, B., and Wilson, C. (2017). Stranded research? Leading finance journals are silent on climate change. *Climatic Change*, 143(1-2):243–260.

Dietz, S., Bowen, A., Dixon, C., and Gradwell, P. (2016). Climate value at risk of global financial assets. *Nature Climate Change*, 6(7):676–679.

Dimson, E., Karakaş, O., and Li, X. (2021). Coordinated engagements. *Available at SSRN 3209072*.

Dimson, E., Karakaş, O., and Li, X. (2023). Coordinated engagements. *European Corporate Governance Institute–Finance Working Paper*, 721(6).

Ding, Y., Sun, C., and Xu, J. (2020). Climate changes and market predictability: Evidence from satellite readings of soil moisture. *Available at SSRN 3637698*.

Doktycz, C. and Abkowitz, M. (2019). Loss and damage estimation for extreme weather events: State of the practice. *Sustainability*, 11(15):4243.

Donadelli, M., Jüppner, M., Paradiso, A., and Ghisletti, M. (2020). Tornado activity, house prices, and stock returns. *The North American Journal of Economics and Finance*, 52:101162.

Dou, W. W., Ji, Y., Reibstein, D., and Wu, W. (2021). Inalienable customer capital, corporate liquidity, and stock returns. *The Journal of Finance*, 76(1):211–265.

Downar, B., Ernstberger, J., Reichelstein, S., Schwenen, S., and Zaklan, A. (2021). The impact of carbon disclosure mandates on emissions and financial operating performance. *Review of Accounting Studies*, 26(3):1137–1175.

Dyck, A., Lins, K. V., Roth, L., and Wagner, H. F. (2019). Do institutional investors drive corporate social responsibility? international evidence. *Journal of Financial Economics*, 131(3):693–714.

Easley, D. and O'hara, M. (2004). Information and the cost of capital. *The Journal of Finance*, 59(4):1553–1583.

El-Haj, M., Alves, P., Rayson, P., Walker, M., and Young, S. (2020). Retrieving, classifying and analysing narrative commentary in unstructured (glossy) annual reports published as pdf files. *Accounting and Business Research*, 50(1):6–34.

El Ouadghiri, I., Guesmi, K., Peillex, J., and Ziegler, A. (2021). Public attention to environmental issues and stock market returns. *Ecological Economics*, 180:106836.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., and Stroebel, J. (2020). Hedging climate change news. *The Review of Financial Studies*, 33(3):1184–1216.

Epstein, L. G. and Schneider, M. (2008). Ambiguity, information quality, and asset pricing. *The Journal of Finance*, 63(1):197–228.

EY (2017). Accounting for the financial impact of natural disasters. Technical report.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, pages 383–417.

Fama, E. F. (1991). Efficient capital markets II. *The Journal of Finance*, pages 1575–1617.

Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, 47(2):427–465.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (2007). Disagreement, tastes, and asset prices. *Journal of Financial Economics*, 83(3):667–689.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Fama, E. F. and MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3):607–636.

Farrell, J. (1995). Talk is cheap. *The American Economic Review*, 85(2):186–190.

Feridun, M. and Gungor, H. (2020). Climate-related prudential risks in the banking sector: A review of the emerging regulatory and supervisory practices. *Sustainability*, 12(13):5325.

Flammer, C., Toffel, M. W., and Viswanathan, K. (2021). Shareholder activism and firms' voluntary disclosure of climate change risks. *Strategic Management Journal*.

Foerster, A. (2019). Climate justice and corporations. *King's Law Journal*, 30(2):305–322.

FRC (2020). Climate thematic review.

Gibson Brandon, R., Glossner, S., Krueger, P., Matos, P., and Steffen, T. (2022). Do responsible investors invest responsibly? *Review of Finance*, 26(6):1389–1432.

Giglio, S., Kelly, B., and Stroebel, J. (2021a). Climate finance. *Annual Review of Financial Economics*, 13(1):15–36.

Giglio, S., Maggiori, M., Stroebel, J., and Weber, A. (2021b). Climate change and long-run discount rates: Evidence from real estate. *The Review of Financial Studies*.

Goldsmith-Pinkham, P., Gustafson, M. T., Lewis, R. C., and Schwert, M. (2023). Sea-level rise exposure and municipal bond yields. *The Review of Financial Studies*, 36(11):4588–4635.

Goldstein, A., Turner, W. R., Gladstone, J., and Hole, D. G. (2019). The private sector's climate change risk and adaptation blind spots. *Nature Climate Change*, 9(1):18–25.

Goldstein, I. and Yang, L. (2017). Information disclosure in financial markets. *Annual Review of Financial Economics*, 9:101–125.

Goldstein, I. and Yang, L. (2019). Good disclosure, bad disclosure. *Journal of Financial Economics*, 131(1):118–138.

Görgen, M., Jacob, A., Nerlinger, M., Riordan, R., Rohleder, M., and Wilkens, M. (2020). Carbon risk. *Available at SSRN 2930897*.

Gostlow, G. (2019). Pricing climate risk. *Available at SSRN 3501013*.

Goyal, A. and Santa-Clara, P. (2003). Idiosyncratic risk matters! *The Journal of Finance*, 58(3):975–1007.

Graff Zivin, J. and Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, 32(1):1–26.

Griffin, P. A., Jaffe, A. M., Lont, D. H., and Dominguez-Faus, R. (2015). Science and the stock market: Investors' recognition of unburnable carbon. *Energy Economics*, 52:1–12.

Griffin, P. A., Lont, D., and Lubberink, M. (2019). Extreme high surface temperature events and equity-related physical climate risk. *Weather and Climate Extremes*, 26:100220.

Guay, W. R. and Verrecchia, R. E. (2018). Conservative disclosure. *Journal of Financial Reporting*, 3(1):73–92.

Hain, L. I., Kölbel, J. F., and Leippold, M. (2022). Let's get physical: Comparing metrics of physical climate risk. *Finance Research Letters*, 46:102406.

Han, Y., Mao, C. X., Tan, H., and Zhang, C. (2024). Climatic disasters and distracted analysts. *Contemporary Accounting Research*, 41(2):1120–1150.

Hansen, L. P., Heaton, J. C., and Li, N. (2008). Consumption strikes back? Measuring long-run risk. *Journal of Political Economy*, 116(2):260–302.

Harnett, E. (2017). The state of climate change knowledge among uk and australian institutional investors. *Sustainable Finance Programme, Smith School of Enterprise and the Environment. The state of climate change knowledge–Working Paper–February.*

Henry, P. B. (2003). Capital-account liberalization, the cost of capital, and economic growth. *American Economic Review*, 93(2):91–96.

Hirshleifer, D. and Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of accounting and economics*, 36(1-3):337–386.

Hong, H. and Kacperczyk, M. (2009). The price of sin: The effects of social norms on markets. *Journal of Financial Economics*, 93(1):15–36.

Hong, H., Karolyi, G. A., and Scheinkman, J. A. (2020). Climate finance. *The Review of Financial Studies*, 33(3):1011–1023.

Hong, H., Li, F. W., and Xu, J. (2019). Climate risks and market efficiency. *Journal of Econometrics*, 208(1):265–281.

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proceedings of the National Academy of sciences*, 107(35):15367–15372.

Hsu, P.-H., Li, K., and Tsou, C.-Y. (2023). The pollution premium. *The Journal of Finance*, 78(3):1343–1392.

Huang, Q., Li, Y., Lin, M., and McBrayer, G. A. (2022). Natural disasters, risk salience, and corporate esg disclosure. *Journal of Corporate Finance*, 72:102152.

Hugon, A. and Law, K. (2019). Impact of climate change on firm earnings: Evidence from temperature anomalies. *Available at SSRN 3271386*.

Huynh, T., Nguyen, T. H., and Truong, C. (2020). Climate risk: The price of drought. *Journal of Corporate Finance*, 65:101750.

Huynh, T. D. and Xia, Y. (2021). Panic selling when disaster strikes: Evidence in the bond and stock markets. *Management Science*.

Ilhan, E., Krueger, P., Sautner, Z., and Starks, L. T. (2023a). Climate risk disclosure and institutional investors. *The Review of Financial Studies*, 36(7):2617–2650.

Ilhan, E., Krueger, P., Sautner, Z., and Starks, L. T. (2023b). Climate risk disclosure and institutional investors. *The Review of Financial Studies*, 36(7):2617–2650.

Ilhan, E., Sautner, Z., and Vilkov, G. (2021). Carbon tail risk. *The Review of Financial Studies*.

In, S. Y., Park, K. Y., and Monk, A. (2017). Is 'being green' rewarded in the market? An empirical investigation of decarbonization risk and stock returns. *International Association for Energy Economics (Singapore Issue)*, 46:48.

Ince, O. S. and Porter, R. B. (2006). Individual equity return data from thomson datastream: Handle with care! *Journal of Financial Research*, 29(4):463–479.

Jegadeesh, N. and Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1):65–91.

Jiang, R. and Weng, C. (2019). Climate change risk and agriculture-related stocks. *Available at SSRN*.

Jouvenot, V. and Krueger, P. (2022). Mandatory corporate carbon disclosure: Evidence from a natural experiment. *Available at SSRN 3434490*.

Karydas, C. and Xepapadeas, A. (2019). Climate change financial risks: Pricing and portfolio allocation. *Economics Working Paper Series*, 19.

Katona, Z., Painter, M., Patatoukas, P. N., and Zeng, J. (2018). On the capital market consequences of alternative data: Evidence from outer space. In *9th Miami Behavioral Finance Conference*.

Krueger, P. (2015). Climate change and firm valuation: Evidence from a quasi-natural experiment. *Swiss Finance Institute Research Paper*, (15-40).

Krueger, P., Sautner, Z., and Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, 33(3):1067–1111.

Kruttli, M. S., Tran, B. R., and Watugala, S. W. (2025). Pricing poseidon: Extreme weather uncertainty and firm return dynamics. *The Journal of Finance*, 80(2):783–832.

Kumar, A., Xin, W., and Zhang, C. (2019). Climate sensitivity and predictable returns. *Available at SSRN 3331872*.

Lamont, O. A. (2001). Economic tracking portfolios. *Journal of Econometrics*, 105(1):161–184.

Lamperti, F., Bosetti, V., Roventini, A., and Tavoni, M. (2019). The public costs of climate-induced financial instability. *Nature Climate Change*, 9(11):829–833.

Landis, C. and Skouras, S. (2021). Guidelines for asset pricing research using international equity data from thomson reuters datastream. *Journal of Banking & Finance*, 130:106128.

Lanfear, M. G., Lioui, A., and Siebert, M. G. (2019). Market anomalies and disaster risk: Evidence from extreme weather events. *Journal of Financial Markets*, 46:100477.

Li, Q., Shan, H., Tang, Y., and Yao, V. (2024). Corporate climate risk: Measurements and responses. *The Review of Financial Studies*, 37(6):1778–1830.

Li, X. (2025). Physical climate change exposure and firms' adaptation strategy. *Strategic Management Journal*, 46(3):750–789.

Lin, C., Schmid, T., and Weisbach, M. S. (2020). Climate change and corporate investments: Evidence from planned power plants. *Fisher College of Business Working Paper (2019-03)*, page 026.

Liu, J., Farag, H., and Farida, S. (2024). Institutional shareholders' networks and greenhouse gas emissions. *Available at SSRN 4745265*.

Liu, L. X., Shu, H., and Wei, K. J. (2017). The impacts of political uncertainty on asset prices: Evidence from the bo scandal in china. *Journal of Financial Economics*, 125(2):286–310.

Lockwood, M. (2013). The political sustainability of climate policy: The case of the uk climate change act. *Global Environmental Change*, 23(5):1339–1348.

Lorenzoni, I., Nicholson-Cole, S., and Whitmarsh, L. (2007). Barriers perceived to engaging with climate change among the uk public and their policy implications. *Global environmental change*, 17(3-4):445–459.

Lucas, E. C. and Mendes-Da-Silva, W. (2018). Impact of climate on firm value: Evidence from the electric power industry in Brazil. *Energy*, 153:359–368.

Lv, M. and Bai, M. (2021). Evaluation of China's carbon emission trading policy from corporate innovation. *Finance Research Letters*, 39:101565.

Matsumura, E. M., Prakash, R., and Vera-Muñoz, S. C. (2024). Climate-risk materiality and firm risk. *Review of Accounting Studies*, 29(1):33–74.

McGlade, C. and Ekins, P. (2015). The geographical distribution of fossil fuels unused when limiting global warming to 2° C. *Nature*, 517(7533):187–190.

Menzly, L. and Ozbas, O. (2010). Market segmentation and cross-predictability of returns. *The Journal of Finance*, 65(4):1555–1580.

Metcalf, G. E. (2009). Market-based policy options to control US greenhouse gas emissions. *Journal of Economic Perspectives*, 23(2):5–27.

Miao, Q. and Popp, D. (2014). Necessity as the mother of invention: Innovative responses to natural disasters. *Journal of Environmental Economics and Management*, 68(2):280–295.

Murfin, J. and Spiegel, M. (2020). Is the risk of sea level rise capitalized in residential real estate? *The Review of Financial Studies*, 33(3):1217–1255.

Nagar, V. and Schoenfeld, J. (2022). Measuring weather exposure with annual reports. *Review of Accounting Studies*, pages 1–32.

Nagar, V. and Schoenfeld, J. (2024). Measuring weather exposure with annual reports. *Review of Accounting Studies*, 29(1):1–32.

NGFS (2020). Overview of environmental risk analysis by financial institution. Technical report.

Nordhaus, W. D. (1977). Economic growth and climate: The carbon dioxide problem. *The American Economic Review*, 67(1):341–346.

Nordhaus, W. D. (1993). Optimal greenhouse-gas reductions and tax policy in the “DICE" model. *The American Economic Review*, 83(2):313–317.

O’Donovan, J., Wagner, H. F., and Zeume, S. (2019). The value of offshore secrets: Evidence from the panama papers. *The Review of Financial Studies*, 32(11):4117–4155.

Painter, M. (2020). An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics*, 135(2):468–482.

Pankratz, N., Bauer, R., and Derwall, J. (2023a). Climate change, firm performance, and investor surprises. *Management Science*, 69(12):7352–7398.

Pankratz, N., Bauer, R., and Derwall, J. (2023b). Climate change, firm performance, and investor surprises. *Management Science*.

Pankratz, N. M. and Schiller, C. M. (2024). Climate change and adaptation in global supply-chain networks. *The Review of Financial Studies*, 37(6):1729–1777.

Pástor, L., Sinha, M., and Swaminathan, B. (2008). Estimating the intertemporal risk–return tradeoff using the implied cost of capital. *The Journal of Finance*, 63(6):2859–2897.

Pástor, L. and Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, 111(3):642–685.

Pástor, L., Stambaugh, R. F., and Taylor, L. A. (2020). Sustainable investing in equilibrium. *Journal of Financial Economics*.

Pástor, L., Stambaugh, R. F., and Taylor, L. A. (2022). Dissecting green returns. *Journal of Financial Economics*, 146(2):403–424.

Pedersen, L. H., Fitzgibbons, S., and Pomorski, L. (2020). Responsible investing: The ESG-efficient frontier. *Journal of Financial Economics*.

Pescaroli, G. and Alexander, D. (2018). Understanding compound, interconnected, interacting, and cascading risks: a holistic framework. *Risk analysis*, 38(11):2245–2257.

Petersen, M. A. (2008). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, 22(1):435–480.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, 22(1):435–480.

Preudhomme, N. A. and Mazzacurati, E. (2020). Asset-level physical climate risk disclosure. In *Values at Work*, pages 67–80. Springer.

Ramelli, S., Wagner, A. F., Zeckhauser, R. J., and Ziegler, A. (2021). Investor rewards to climate responsibility: Stock-price responses to the opposite shocks of the 2016 and 2020 US elections. *Review of Corporate Financial Studies*.

Rao, S., Koirala, S., Thapa, C., and Neupane, S. (2021). When rain matters! Investments and value relevance. *Journal of Corporate Finance*, page 101827.

Rapier, R. (2020). Fossil fuels still supply 84 percent of world energy—and other eye openers from BP's annual review.

Rehse, D., Riordan, R., Rottke, N., and Zietz, J. (2019). The effects of uncertainty on market liquidity: Evidence from Hurricane Sandy. *Journal of Financial Economics*, 134(2):318–332.

Ricci, E. C. and Banterle, A. (2020). Do major climate change-related public events have an impact on consumer choices? *Renewable and Sustainable Energy Reviews*, 126:109793.

Ross, S. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, 13(3):341–360.

Rosvold, E. L. and Buhaug, H. (2021). Gdis, a global dataset of geocoded disaster locations. *Scientific Data*, 8(1):1–7.

Sautner, Z., Van Lent, L., Vilkov, G., and Zhang, R. (2023a). Firm-level climate change exposure. *The Journal of Finance*, 78(3):1449–1498.

Sautner, Z., Van Lent, L., Vilkov, G., and Zhang, R. (2023b). Pricing climate change exposure. *Management Science*, 69(12):7540–7561.

Schimanski, T., Bingler, J., Hyslop, C., Kraus, M., and Leippold, M. (2023). Climatebert-netzero: Detecting and assessing net zero and reduction targets. *arXiv preprint arXiv:2310.08096*.

Schlenker, W. and Taylor, C. A. (2021). Market expectations of a warming climate. *Journal of Financial Economics*.

Semieniuk, G., Campiglio, E., Mercure, J.-F., Volz, U., and Edwards, N. R. (2021). Low-carbon transition risks for finance. *Wiley Interdisciplinary Reviews: Climate Change*, 12(1):678.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3):425–442.

Shiller, R. J. (2020). Narrative economics: How stories go viral and drive major economic events.

Shive, S. A. and Forster, M. M. (2020). Corporate governance and pollution externalities of public and private firms. *The Review of Financial Studies*, 33(3):1296–1330.

Tang, S. (2022). Why do companies not disclose climate change adaptation strategies? *Available at: https://assets.researchsquare.com/files/rs-1362845/v1_covered.pdf?c=1647540074*.

Tankov, P. and Tantet, A. (2019). Climate data for physical risk assessment in finance. *Available at SSRN 3480156*.

Thomä, J. and Chenet, H. (2017). Transition risks and market failure: a theoretical discourse on why financial models and economic agents may misprice risk related to the transition to a low-carbon economy. *Journal of Sustainable Finance & Investment*, 7(1):82–98.

Tol, R. S. (2009). The economic effects of climate change. *Journal of Economic Perspectives*, 23(2):29–51.

Touboul, S., Glachant, M., Dechezleprêtre, A., Fankhauser, S., and Stoever, J. (2023). Invention and global diffusion of technologies for climate change adaptation: a patent analysis. *Review of Environmental Economics and Policy*, 17(2):316–335.

Trinks, A., Mulder, M., and Scholtens, B. (2020). An efficiency perspective on carbon emissions and financial performance. *Ecological Economics*, 175:106632.

Tsang, A., Xie, F., and Xin, X. (2019). Foreign institutional investors and corporate voluntary disclosure around the world. *The Accounting Review*, 94(5):319–348.

Tversky, A. and Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. *Cognitive psychology*, 5(2):207–232.

Venturini, A. (2022). Climate change, risk factors and stock returns: A review of the literature. *International Review of Financial Analysis*, 79:101934.

Verrecchia, R. E. (1983). Discretionary disclosure. *Journal of Accounting and Economics*, 5:179–194.

Verrecchia, R. E. (2001). Essays on disclosure. *Journal of accounting and economics*, 32(1-3):97–180.

Wagner, A., Deng, M., Leippold, M., and Wang, Q. (2023). War and policy:

Investor expectations on the net-zero transition. *Swiss Finance Institute Research Paper*, (22-29).

Weitzman, M. L. (2009). On modeling and interpreting the economics of catastrophic climate change. *The Review of Economics and Statistics*, 91(1):1–19.

Xu, Q. and Kim, T. (2021). Financial constraints and corporate environmental policies. *The Review of Financial Studies*.