Does disclosure of climate adaptation pay?

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Abstract

This work analyses the firm value implications of companies' adaptation to physical climate risks. We constructed and validated a text measure from the UK annual reports, proxying for worldwide exposure to natural disasters. We show that natural disasters have a negative effect on firm value, especially domestic rather than foreign events. Disclosing firms hit by a natural disaster attenuates these negative value effects, a result in line with the benefits of climate disclosure. In contrast, impacted firms mentioning to adapt to physical climate risks were evaluated on par with not-disclosing firms. We show that these negative value effects are driven by higher investor ambiguity after natural disaster events for both not disclosing and proactive disclosing firms. Our results have important implications for policies aimed at fostering the generalised disclosure of climate adaptation in companies' annual reports.

Keywords: Climate Change, Physical Risk, Adaptation, Annual Reports, Firm Value

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1. Introduction

Adapting to changing business environments is a natural feature of corporations. A large literature in corporate finance analysed how firms can adapt to evolving industry conditions (Hoberg & Phillips, 2010), or different institutional environments (Öztekin & Flannery, 2012), and the effect of these strategies on firm value (Adam et al., 2007). The stochastic evolution of near- and long-term risks associated with climate change will likely require firms to reshape many of their strategic operations in the coming decades. However, little is known about the causal effect of firms' adaptation to climate change risks on firm value.

Recent climate events worldwide are making tangible the threats of a warming world for companies' operations. For instance, in 2018, the first bankruptcy 'because of climate change' occurred in the US.[2] Furthermore, the extreme temperatures registered around the world in 2022 indicate that physical climate risks should not be confined only to agricultural or related sectors.[3] This anecdotal evidence has been empirically confirmed from recent literature on climate finance, which has shown how physical risks historically correlate with firm-level outcomes. In particular, it has been shown that physical risks should neither be limited to only temperature risks (Huynh & Xia, 2021), nor be thought to belong only to specific industries (Addoum et al., 2021). Moreover, given that physical climate risks may impact both supply and demand channels in different parts of the world (Pankratz & Schiller, 2021), it is likely that several companies in several sectors are exposed to various degrees to threats of climate change. The way in which companies will manage to adapt to climate risks will dictate losers and winners from climate change in the coming decades.

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

[3] See, for instance, the effects of extreme temperature on the ski industry in Europe at the end of 2022: https://www.euronews.com/green/2023/01/04/no-snow-europes-ski-resorts-forced-to-close-amid-record-breaking-temperatures

While the recent literature on climate finance focuses on analysing the effects of mitigation measures to climate transition risks on firm value (Li et al., 2022), little is known about how investors evaluate firms' efforts to manage their physical climate risk exposure. However, this is a concern for governments and regulators given the expected financial flows for climate adaptation strategies in the coming years.[4] All of these issues motivate us to empirically examine the firm value implications of companies' adaptation to physical climate risk, which has been a gap in the climate finance literature thus far.

To study the empirical relationship between firm adaptation to climate change risks and firm value, we construct different measures of exposure and adaptation to physical climate risks using annual reports data for UK companies listed on the London Stock Exchange. We use textual information from the annual reports of UK companies in our analysis for several reasons. First, the UK has been one of the most pioneering countries in regulating firm-level climate change disclosure (Jouvenont and Krueger, 2022). This set a natural groundwork to analyse how investors evaluate during time the cross-sectional evolution in climate adaptation practices of UK firms. Moreover, all companies listed on the London Stock Exchange (LSE) are legally required to fill an annual report every year. This is important, as our sample may mitigate possible selection bias concerns that may arise when focussing on *voluntary* disclosure (such as earning conference calls, Li et al., 2022).

We measure physical climate risk and adaptation based on the share of conversations on annual reports related to climate and weather keywords, following three steps. We first retrieve natural disaster keywords provided from the SENDAI Framework for Disaster Risk Reduction. We further enrich this list from sources including Meteorology books and Wikipedia

[4] See, for instance, the programme on global adaptation launched at the COP26: https://unfccc.int/process-and-meetings/the-paris-agreement/the-glasgow-climate-pact/cop26-outcomes-finance-for-climate-adaptation#At-COP26,-a-work-programme-on-the-global-goal-on-a

lists. For each unigram, we manually screened the top 3,000 associated bigrams that appeared in the annual reports to reduce the possibility of counting false positives. We follow a similar approach to identify firms that are more proactive in managing their exposure to physical climate risks following the methodology suggested by Li et al. (2022). The n-gram approach we employ in the paper is similar to those used by prior studies (Li et al., 2022; Sautner et al., 2022). Moreover, as we show in this study, the n-gram approach may be useful in analysing textual sources that are not standardised across firms (as is the case for UK annual reports). To validate our text measure, we further combine textual information with financial and geo-spatial data related to firm locations and natural disasters. Specifically, we retrieved firm location data for about 2,400 UK parents' headquarters and 39,000 subsidiaries in the UK or worldwide. We then spatially merge these locations with natural disaster polygons provided by the Geocoded Disasters (GDIS) dataset (Rosvold & Buhaug, 2021). Importantly, GDIS provides us information at the specific administrative level where a natural disaster happened, allowing us to identify, for each event, the granularity of the impact.

Before analysing the implications of climate adaptation disclosure on firm value, we first examine whether the text measures capture material exposure to physical climate risk. Multivariate tests show that the presence of natural disasters at one foreign or domestic firm location is positively correlated with a significant increase in our climate text measure. Our results also show that the magnitude of the relationship is driven significantly from domestic rather than foreign impacts. This results, as shown in the climate finance literature, may be coherent with the proprietary costs dictated by climate change disclosure (Ilhan et al., 2023).

We then examine the firm value implications of companies' exposure around natural disaster events by means of an event study methodology. For our identification strategy, we classify treatment companies as those companies with a firm location in a disaster area. For each event, we compute the cumulative market-adjusted returns for treatment and control firms over the [-5,+5] period. Our event study analysis leads the following important conclusions. First, we show that natural disasters have a negative and significant impact on firm value for domestic rather than foreign events. Moreover, the negative impact on firm value is better identified when we focus on the second (i.e., county) rather first administrative level (i.e., country), with a decrease in market-adjusted returns of about 200 bps. Second, we found that impacted firms disclosing more than average about their exposure to natural disasters were positively rewarded from the market, with a *lower* loss in value of 110 bps compared to not disclosing firms. If firm proactiveness to physical climate risks pays off when the effects of natural disasters materialize, one would expect these results to be driven from climate-resilient firms. However, our third result is that impacted firms disclosing to act in a proactive way against physical climate risks were valued on par with not disclosing firms. In other words, only the climate risk disclosure component seems to be positively priced in the UK equity market.

We test three different hypotheses to explain the results we document from the event study analysis. As it is known from the asset pricing literature, a decrease in equity prices after a specific event (e.g., a natural disaster) may be caused by a decrease in expected cash flows or by an increase in the discount rate. A third, and more subtle, explanation may be related to the low sustainability compliance of firms that disclose climate adaptation in their annual reports. If investors grasp climate adaptation disclosure as a form of greenwashing strategy, then one would not expect proactive firms to be rewarded from the market, especially when hit by a natural disaster. Overall, results are consistent with the presence of a higher climate risk ambiguity during natural disaster events, especially for not disclosing and proactive disclosing firms, in line with the discount rate news hypothesis. Therefore, the climate ambiguity premium we document is not purely driven by investors' expectations of decreasing cash flows or firm greenwashing strategies, but rather by the change in the discount rate following an increase in climate risk uncertainty.

Our work makes several important contributions to the climate finance literature. Our first contribution is related to the dynamics underlying climate risk disclosure. In particular, our results suggest that firms disclose their material physical climate risk to investors. However, our results also highlight the relevance for regulators to balance the needs of investors (requiring higher firm transparency), and the proprietary costs suffered by firms when disclosing their climate physical risk exposure (Ilhan et al., 2023). Moreover, our paper contributes to the literature that studies the pricing of climate risks in financial markets, and to the debates about the relationship between physical climate risk disclosure and firm value. Coherently with previous results documenting a negative relationship between natural disaster exposure and firm value in the US (Huynh & Xia, 2021; Nagar & Schoenfeld, 2022), we confirm that investors penalized firms impacted by natural disasters. However, differently from these studies, we show that investor evaluate *positively* physical climate risk disclosure. Finally, our most timely contribution is related to the firm value implications of climate adaptation reporting. Interestingly, our results are antithetical to the one of Li et al. (2022) that focus on transition climate risk. Specifically, Li et al. (2022), on the one hand, showed the presence of a *negative* relationship between firm value and climate transition risk for US companies. Moreover, Li et al. (2022) found that only firms that do not respond proactively to climate transition risks were value at discount. Our results have therefore important implications for policies aimed to foster the generalized disclosure of climate adaptation practices in companies' annual reports.

The remainder of this paper is organised as follows. Section 2 described the actual regulatory environment about climate disclosure in the UK. Section 3 presents our hypotheses. Section 4 describes the data. Section 5 describes the two physical climate risk measures used in this study and introduces the climate adaptation measures used in asset pricing tests. Section

6 presents and discusses the results of the study. Section 7 provides three possible explanations for our results. Finally, Section 7 concludes the paper.

2. Background: Climate Change Disclosure in UK Annual Reports

Over the past decades, the United Kingdom has been one of the most pioneering countries in regulating firm-level climate change disclosure (Jouvenont and Krueger, 2022). This regulatory effort underlies the more general strategy of the UK Government to gain worldwide leadership in the climate change policy arena (Lorenzoni et al., 2007). In line with this, the UK carried out a series of regulatory acts aimed at binding domestic policies to the outcomes of several international climate negotiations (e.g. the Kyoto Protocol), as well as the scientific findings of the Intergovernmental Panel on Climate Change (IPCC). Therefore, regulation of climate disclosure at the firm level represents one of the regulatory tools to align corporate behaviour with UK commitments towards climate change policies.

Most UK policy efforts have focused on reducing domestic carbon emissions (Bowen and Rydge, 2011). In particular, the 2008 Climate Change Act made the UK the first country worldwide to set legally binding carbon budgets, aiming to cut UK emissions by 80% by 2050, with respect to the 1990 baseline (Climate Change Act, 2008). Accordingly, the focus of corporate regulations on climate disclosure in the UK has been related mainly to carbon reporting practices. The most relevant regulation in this regard is the Companies Act 2006 (Strategic and Directors' Reports) Regulations 2013. Under this regulation, all UK incorporated firms, regardless of industry affiliation, were obliged to disclose carbon emissions information in their annual reports.[5] The ultimate goal of the regulation was to indirectly elicit a decrease

[5] More specifically, the regulation was referred to all UK incorporated and whose equity shares are listed on the Main Market of the London Stock Exchange UK or in an EEA State or admitted to trading on the New York Stock Exchange or NASDAQ Stock Market (Jouvenont and Krueger, 2022).

in corporate emissions by pressuring firms "to think about ways in which these can be reduced".[6] Recent literature on corporate finance has confirmed the real effects of carbon disclosure transparency in UK's annual reports. In particular, both Downar et al. (2021) and Jouvenont and Krueger (2022) provide evidence that UK firms affected by the aforementioned regulation reduced their emissions relative to a control group of European firms. Moreover, Jouvenont and Krueger (2022) also showed that the regulation had firm value effects in that investors *penalised* disclosing firms with high levels of disclosed GHG emissions. Jouvenont and Krueger (2022) explain such evidence in light of investors' anticipation of higher future costs for firms with high levels of carbon risk. In general, the results of Jouvenont and Krueger (2022) are in line with other climate finance studies that show a negative relationship between firm value and disclosed corporate emissions (for example, Bolton and Kacperczyk, 2021).

As a consequence of this policy's focus on domestic mitigation strategies, UK regulations regarding physical climate risks and adaptation disclosure have been coarser. Regarding the former, for instance, there is no equivalent of the SEC 2010 Climate Change Guidance for UK listed firms.[7] Instead, the disclosure of physical climate risks in UK annual reports is expected to follow the general guidelines provided by the international accounting standards for natural disaster reporting (EY, 2017). However, several regulatory surveys showed that disclosure of physical risks in UK annual reports "often lacked substance", and that investors find "still difficult to understand how the company intends to respond to the climate-related risks and opportunities it faces" (FRC, 2020). This evidence has been corroborated by a recent grey literature that highlights different areas of improvement in physical climate risk-reporting practices for UK firms (e.g., Deloitte, 2019). The UK Government has recognised the more general need for increased transparency in climate disclosure in UK annual reports (not only

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[6] See: https://www.gov.uk/government/news/better-and-simpler-company-reporting
[7] As explained in Kim et al. (2022), the SEC was the first regulatory body worldwide to release mandatory rules for climate disclosure for US firms. Ceres (2014) defined the regulation as "a milestone on the path towards better corporate reporting of material climate issues".

on the physical risk side), and in 2019, presented its Green Finance Strategy. Among other goals, the strategy includes the expectation that UK listed companies and large asset owners should disclose in line with the Taskforce on Climate-related Financial Disclosures (TCFD) recommendations by 2022.[8]

With respect to climate adaptation reporting, the only regulatory tool available to the UK Government to influence adaptation disclosure practices is represented by the 'Adaptation Reporting Power' (ARP). The ARP was introduced with the Climate Change Act 2008 to ensure through a National Adaptation Programme that firms, and society in general, are becoming more resilient to climate change risks. In particular, the Climate Change Act 2008 provides the Secretary of State the power to direct "reporting authorities" (i.e., those entities that are issued with Directions to report from the Secretary of State) to produce specific reports where they explain their strategies to adapt to climate change. The ARP runs through a five-year cycle and allows its applications to be changed from cycle to cycle. In fact, both the regulatory requirements and the group of reporting authorities initially identified in the first cycle changed significantly over the years.[9]

The features outlined thus far about adaptation disclosure highlight two important differences with respect to carbon reporting in UK annual reports. The first pertains to which firm is expected to disclose a specific type of climate-related information. As mentioned above, while all UK firms need to disclose their carbon emissions, only a specific subgroup of selected companies needs to report on climate adaptation. Moreover, this group of reporting authorities may change according to the specific ARP round. On the one hand, such an approach was introduced to allow the government more flexibility in applying the ARP according to the

[8] For more information, see:
https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1056085/mandatory-climate-related-financial-disclosures-publicly-quoted-private-cos-llps.pdf
[9] The updated list of organisations reporting under the ARP (third round) is reported here:
https://www.gov.uk/government/publications/climate-change-adaptation-reporting-third-round/list-of-organisations-reporting-under-adaptation-reporting-power-third-round

specific regulatory requirements at the time. However, this kind of government flexibility may come at the price to induce uncertainty at the firm and investor levels. Regarding the former, it is known from corporate finance literature that changes in regulation (and thus policy uncertainty) may hinder firm investment strategies (Fuss et al., 2008). Regarding the latter, it is known from asset pricing literature that political uncertainty at the firm level may induce ambiguity in investor evaluations (Liu et al., 2017). The second main difference is related to the specific textual source from which UK companies are expected to disclose climate information. Specifically, firm GHGs emissions are now expected to be *mandatorily* disclosed annually in companies' annual reports. However, the actual regulatory framework allows reporting authorities to attend an ARP round *voluntarily*. More importantly, reporting authorities are *not* mandated to disclose any information in their annual reports after a specific ARP round. Thus, under actual regulatory settings, a reporting authority is allowed to *voluntarily* disclose its corporate strategies to investors to adapt to climate change.

To summarise, climate change disclosure in UK annual reports was regulated with a specific focus on carbon reporting practices. Recent research shows the real- and firm-value effects of this type of firm disclosure (Downar et al. 2021; Jouvenont and Krueger 2022). However, little is known about UK firms' climate risk and adaptation disclosure practices, and how investors price these kinds of disclosures. This study aims to shed light on these issues empirically.

3. Hypothesis Development

Our main hypotheses rely on the idea that physical climate risk disclosure is likely to affect the value of UK firms. Before delving into the specific channels in which climate disclosure may affect firm value, it is important to clearly define physical climate risk disclosure and explain why it may be relevant to investors. As for other types of company disclosure, UK firms are expected to report the effects of natural disasters in their annual reports if they are deemed material for companies' operations (EY, 2017). Although the majority of studies in climate finance have analysed the effects of climate physical risks on the cash flows of US firms (Addoum et al., 2021; Huynh & Xia, 2021), we have reasons to believe that UK firms are also exposed to the material threats of natural disasters, both nationally and worldwide. For instance, a recent survey of firms in the S&P100 (which also contains companies in our sample) found that "extreme weather has always been a business risk to manage, and it is considered when companies evaluate (…) facility sites, logistics, and backup power needs" (Crawford & Seidel, 2013). In line with this, the recent literature on climate finance has shown how physical risks historically correlate with firm-level outcomes. In particular, it has been shown that physical risks should neither be limited to only temperature risks (Huynh & Xia, 2021), nor be thought to belong only to agricultural or related sectors (Addoum et al., 2021). Moreover, given that physical climate risks may impact both the supply and demand channels in different parts of the world (Pankratz & Schiller, 2021), it is likely that several companies in different sectors are exposed to various degrees to physical risks. If the impacts of natural disasters are material to companies' operations, we would expect exposed companies to disclose these events in their annual reports to investors. Thus, we formulated our first hypothesis as follows:

H1*: The realisation of natural disasters at the firm level leads to an increase in physical climate risk disclosure.*

Hypothesis 1, although intuitive, is critical for our empirical tests, as it provides the natural groundwork to investigate how investors evaluate physical climate risk disclosure. However, the firm value implications of this type of disclosure are not clear in advance. The recent literature on climate finance provides contrasting evidence with respect to the effects of physical climate risk disclosure on firm value. On the one hand, studies (that mainly focus on the US market) found that disclosing companies are valued at discounts (Berkman et al., 2021; Nagar & Schoenfeld, 2022). On the other hand, recent studies have revealed the beneficial effects of disclosing these kinds of risks to investors (Matsumura et al., 2022; Schiemann and Sakhel, 2019).[10] As explained in Section 2, in contrast to the US, regulation of physical climate risk reporting in the UK is still in its infancy, and firms hold a lot of discretion about the type of climate risk information disclosed to investors. This reluctance to disclose should be framed by considering the proprietary costs associated with climate change disclosure (Ilhan et al., 2023). Specifically, disclosing the impact of natural disasters at a particular firm location could be "costly" for a company, as this information may reveal proprietary information about specific firm operations (Tang, 2022). Considering both climate regulation and proprietary cost uncertainty, *voluntary* firm transparency about climate exposure may be positively rewarded by investors. Therefore, we derive the following hypothesis from models that predict a positive relationship between firm value and voluntary disclosure (Banghøj and Plenborg, 2008):

H2*: There is a positive relationship between physical climate risk disclosure and firm value.*

An additional reason for the positive relationship between climate disclosure and firm value may be related to firms' proactiveness in managing their physical risk exposure. A large body of corporate finance literature explores the effects of firm strategies on firm value in managing exchange rate risk (Eaker & Grant, 1987), operational risk (Carter et al., 2006), and transition risks related to a green economy (Li et al., 2022). However, little is known about the value implications of firms' adaptation to physical climate risks. A natural scenario to analyse whether climate adaptation disclosure has a positive effect on firm value is to analyse how investors evaluate this information when a firm is hit by a natural disaster. If climate adaptation strategies pay off when the effects of climate change materialise, one would expect only

[10] The reader is referred to the work of Venturini (2022) for the recent debates about climate risk pricing in the equity market.

proactive firms to be rewarded from the market. However, a recent interview with 60 managers of the FTSE100 (that are part of our sample) noted that UK firms are particularly *reluctant* to mention their climate adaptation strategies in their annual reports (Tang, 2022). In effect, 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. 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." Bond and Zeng (2022) generalise this idea more formally in a theoretical model in which they predict that firms prefer not (or only partially) disclose voluntary information if they are uncertain about investors' preferences over that disclosure. Therefore, we derive the following hypotheses regarding firms' transparency to physical climate risks, climate adaptation disclosure, and firm value:

H3*: The positive relationship between physical climate risk disclosure and firm value is driven only by the benefits of reporting climate change risk.*

There may be several alternative reasons why climate adaptation disclosure may not pay off when a firm is affected by natural disasters. First, investors may evaluate a firm's proactiveness to physical climate risks as a direct consequence of company exposure to natural disasters. This scenario may be coherent with the evidence found in the literature that physical climate risks may be more harmful for specific firms rather than others (Addoum et al., 2021). More in general, considering a simple discounted cash flow model, firm value has a *direct* relationship with expected cash flows, and an *indirect* relationship with expected discount rates. Regarding the former relationship, investors' expectations about future cash flows can be inferred from analysts' earnings forecasts after a natural disaster event (cash flow news hypothesis). If these forecasts drop on average after a natural disaster, this evidence would be coherent with investor anticipation of decreasing future cash flows for impacted firms. Importantly, the cash flow hypothesis further predicts that expected cash flows will drop to a greater extent for firms that disclose climate adaptation strategies. The cash flow hypothesis is as follows:

***H4A**: The cash flow hypothesis predicts that expected cash flows drop after a natural disaster, both for not disclosing and proactive disclosing firms.*

The relationship between expected discount rates and firm value can be inferred analysing the resultant uncertainty around an event of interest (discount rate news hypothesis). In our context, it is important to distinguish two different types of uncertainty that may arise in financial markets. As explained in Rehse et al. (2019), both risk and uncertainty refer to a scenario in which investor information about a future event is limited. The main theoretical difference is that risk is referred to be the measurable part of this limited information. In contrast, ambiguity (also known as Knightian uncertainty (Knight, 1929)), is perceived to be the immeasurable part.[11] To differentiate between these two channels, we investigate two different proxies of uncertainty. Regarding the risk explanation, it may be the case that the realization of natural disasters at a specific firm location leads an increase in the market price of risk. Therefore, if the negative return during a natural disaster is caused by increasing risk, we would expect stock return volatility to increase over the same period. Moreover, the climate risk explanation further predicts that the increase in volatility affects also for firms disclosing climate adaptation strategies. The climate risk hypothesis predicts the following:

***H4B**: The climate risk hypothesis predicts that stock volatility will increase after natural disasters, both for not disclosing and proactive disclosing firms.*

Regarding the ambiguity explanation, Rehse et al. (2019) showed that during times of higher ambiguity in the equity market, stock liquidity tends to be lower. Given that ambiguity aversion

[11] In probabilistic terms, ambiguity is the lack of knowledge about the true probability distribution. Risk on the other hand refers to probabilistic consequences of decisions under a known probabilistic distribution.

is priced in the cross-section of stock returns (Brenner and Izhakian, 2018), a decrease in liquidity after a natural disaster would be coherent with a higher risk premium required by investors for impacted firms. Moreover, while firm transparency regarding its physical climate risk exposure may reduce ambiguity about the true effects of natural disasters for companies' operations, the same may not hold for climate adaptation disclosure. The climate ambiguity hypothesis predicts the following:

***H4C**: The climate ambiguity hypothesis predicts that stock liquidity will decrease after natural disasters, both for not disclosing and proactive disclosing firms.*

A final (and more subtle) possibility is related to the fact that climate adaptation disclosure may not reflect real firms' commitments in managing their climate risk exposure. This idea would be coherent with a recent literature that found that firms may not "walk the talk" when disclosing climate sustainability efforts in their annual reports (Raghunandan & Rajgopal, 2020; Bingler et al., 2023). Therefore, the reason to appear "climate-proof" to investors may denote firm's willingness to divert attention from other sustainability issues that may be value relevant for their shareholders (Huynh & Xia, 2021). If this is the case, then climate adaptation disclosure may instead proxy for some kind of greenwashing strategy. However, if investors would grasp these kinds of firm misconduct, one will not expect climate adaptation disclosure to be rewarded from the market, especially when hit by a natural disaster. The greenwashing hypothesis is stated as follows:

***H4D**: The greenwashing hypothesis predicts that firms using a more proactive tone in describing their climate risk exposure are more likely to incur in sustainable related violations.*

4. Data and Descriptive Statistics

To measure firm-level exposure and responses to physical climate risks, we combined textual, financial, and geospatial data related to firm locations and natural disasters from four main sources. The final sample covers around 23,000 annual reports of more than 2,000 UK incorporated firms listed on the London Stock Exchange (LSE). In this section, we describe each of the datasets used in our analysis and provide quantitative and graphical evidence relevant to the empirical tests.

4.1 UK Annual Reports

We retrieve annual reports for all UK LSE Main Market and AIM firms in a PDF format for fiscal year-ends between January 1996 and December 2018.[12] As described by El-Haj et al. (2020), a generic UK annual report can be divided into two main sections. The first section is related to the narrative component, where management qualitatively discloses the key facts that occurred during the fiscal year. The second section is related to mandatory financial statements, footnotes, and other statutory information, where management provides quantitative and regulatory-related information. A manual reading of a sample of UK annual reports indicates that management discloses physical climate risk information in both types of sections. Therefore, similar to Nagar & Schoenfeld (2022) for US 10-K filings, we use both sections of an

[12] We would have liked to extend the time series related to annual reports even further. However, we noticed that several annual reports in the Companies House database before the 1996 are not automatically available but need the payment of a certain fee before being downloaded. However, several authors empirically showed that climate change concerns are a recent phenomenon in capital markets (Engle et al., 2020; Huynh & Xia, 2021), thus questioning about the usefulness of constructing longer estimation windows when analysing climate risks at the firm level. Finally, as we explain in Section 4.4, we limit the sample period to 2018 because natural disasters data are available until that specific year.

annual report to capture all the different firm-level dynamics related to exposure and responses to physical climate risks.

We use Thomson Reuters Eikon as our main source of textual data and rely on Companies House only if a generic annual report is missing in a given year. In Thomson Reuters Eikon, PDF files 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 us with only fully scanned PDFs files. Therefore, we developed an algorithm capable of identifying each of these cases with full accuracy. If the PDF file is digitally created, we simply extract text from the annual reports using text-mining modules in Python. In the other two cases, we apply Optical Character Recognition (OCR) algorithms in order to prepare annual reports for textual analysis. Importantly, we apply text pre-processing techniques (such as binarisation and skew correction) when processing semi-or fully scanned PDF files. The aim of these techniques is to ensure the highest quality of the textual source before applying OCR algorithms to extract the text in a digital format.[13]

Thus far, the literature on climate finance has used different textual sources to proxy for physical climate exposure at the firm level, such as newspapers (Engle et al., 2020), conference calls (Li et al., 2022; Sautner et al., 2022), and CDP disclosure (Ilhan et al. 2021). However, we consider the employment of annual reports in our setting as an advantage for at least two reasons. First, all companies listed on the LSE are legally required to fill an annual report every year. This is important, as our sample may mitigate possible selection bias concerns that may arise when focusing on textual sources that are voluntary in nature (such as earning conference calls or CDP disclosure). Second, unlike US 10-K filings, the disclosure templates of UK annual

[13] It is known that textual files processed via OCR algorithms may suffer of measurement error even after text-processing techniques (El-Haj et al., 2020). In particular, there could be some inaccuracy when the OCR algorithm tries to detect specific words in a generic annual report. However, the direction of this potential measurement error is likely to bias our estimates in Section 6.1 against finding significant results.

reports are unstandardised, and management is left with a high level of discretion in locating and structuring the information reported (El-Haj et al., 2020). Therefore, this kind of discretion in UK annual reports allows us to better identify cross-sectionally the heterogeneity in disclosed climate adaptation strategies.

4.2 Stock Returns and Firm Characteristics

We retrieved data on stock returns and industry affiliation from Thomson Reuters DataStream. As noted from a large literature in finance, Thomson Reuters DataStream may suffer from data errors (Choi et al., 2020; Hou et al., 2011; Ince & Porter, 2006, among others). Therefore, we constructed our sample of UK listed companies following the data-filtering guidelines provided by Landis & Skouras (2021).[14] These guidelines carefully build on previous recommendations provided in the asset pricing literature, such as those described by Hou et al. (2011) and Ince & Porter (2006).

To identify a specific industry affiliation, we rely on the Industry Classification Benchmark (ICB). The ICB is the metric used to classify companies listed on the London Stock Exchange.[15] Importantly, we exclude all firms belonging to the "Financials" ICB category from our main analysis. Filtering out financial companies (such as banks and insurance firms) allows us to focus our analysis only on firms that may make use of hedging instruments against physical climate risk and not on their providers (Li et al., 2022).

We further collect accounting data in British Pound (GBP) from Worldscope, Financial Analysis Made Easy (FAME), and Compustat Global. Following Jouvenot & Krueger (2022), we

[14] We refer the reader to Table 1 in Landis and Skouras (2021) to understand the 21 filters applied in our analysis to clean stock returns data.
[15] See: https://www.ftserussell.com/data/industry-classification-benchmark-icb

exclude firm-year observations with annual sales growth greater than 500% and negative assets or sales. Moreover, we obtained data on firms' fiscal-year-end reporting schedules to correctly merge yearly financial records with textual annual report information. Finally, to discern about the cash-flow and discount rate hypotheses in our empirical tests, we also gather data from the Institutional Brokers' Estimate System (IBES) on analysts' forecasts. Table 1 provides summary statistics for the main variables used in the analysis, while Appendix A.1 provides definition of these variables.

4.3 Corporate Ownership Structure and Firm Locations

We consider corporate ownership linkages between UK parents and their worldwide subsidiaries, using FAME as our main source. It is important to note that information about the corporate ownership structure in FAME is static at the time of download. Therefore, we used textual information provided in companies' annual reports to create a *dynamic* ownership structure throughout the period of analysis. Such an approach is appropriate given that UK listed firms are expected to comply with the "Regulation SI 2015/980".[16] Following the literature on corporate governance, we identify a firm as a parent if it holds more than 20% of voting rights in a specific subsidiary in a generic year (Aminadav & Papaioannou, 2020). Then, for each firm, each year, we checked whether a specific subsidiary name (as provided in FAME) was mentioned in the annual report of its parent listed company. To operationalise this, we follow O'Donovan et al. (2019) and allow a maximum threshold of the generalised edit (or Levenshtein) distance of 80% between the subsidiary name and how such a string appears in

[16] 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 to focus only on the most relevant holdings before the law came into effect.

the parent's annual report.[17]Out of the nearly 50,000 subsidiaries retained after applying the set of filters described above, we identify around 38,000 UK subsidiaries throughout the analysis period.

Moreover, we obtain firm location data about parents' headquarters and their subsidiaries using addresses from FAME. If the locations of parent headquarters or one of its subsidiaries is missing, we further manually check the data and add information retrieving data from Dun & Bradstreet and country-specific news websites. We then transformed the address names into geographic coordinates using the OpenStreetMap API. Panel A of Figure 1 shows the geographical distribution of UK parent headquarters and their subsidiaries worldwide. As Figure 1, Panel A, shows, the distribution of subsidiaries is concentrated in G7 countries (i.e., Canada, Germany, France, Italy, Japan, UK and the United States), accounting for 73.72% of the total subsidiaries' locations. Figure 2, Panel A, shows the geographical distribution of parent headquarters and their subsidiaries in the UK. Notably, although the majority of the firm locations are located in the Greater London Area, there is significant geographical dispersion of companies' headquarters and subsidiaries in the country.

4.4 Natural Disasters

Finally, we gathered data on natural disasters from the Geocoded Disasters (GDIS) dataset (Rosvold & 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 both the environmental and climate finance literature (Pankratz & Schiller, 2021). By merging the EM-DAT dataset with GDIS, we

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

can retrieve information about: (i) the type of natural disaster event;[18] (ii) the spatial geometry in the form of GIS polygons for different administrative entities listed as "disaster locations" in the EM-DAT dataset;[19] (iii) economic (dollar) damages caused by each event; (iv) day, month, and year of the natural disaster event. We applied the following filters to the merged GDIS/EM-DAT dataset. First, we convert the economic dollar amounts in EMDAT in British pounds, and, following Huynh and Xia (2021), we require that an event caused at least £10 million in 2018 constant pounds. Second, we retain only natural disasters related to one of the following categories: (i) meteorological; (ii) hydrological; or (iii) climatological. Thus, we filter out geophysical disasters, given their uncertain relationship with climate change.[20]

Based on the natural disaster polygons in GDIS, we spatially merged the locations of parents' headquarters and their subsidiaries to the affected areas. It is important to note that we have different degrees of choice when applying the spatial merge between firm locations and areas affected by a natural disaster. In particular, GDIS provides three types of geographical granularities according to the specific administrative unit hit by a natural hazard in a country. The first type of polygon is related to the first administrative division of the country where a natural disaster happened in a certain year. Although the area of this administrative level may vary across countries, this kind of information is still more granular than focussing only on country level impacts. GDIS also provides us polygons for the second and third administrative level where a natural disaster happened in a given year. However, there is great heterogeneity in the level of coverage about the granularity of the administrative units impacted worldwide. Therefore, given that the number of firm locations affected at the third administrative level is

[18] EM-DAT includes all the disasters (not only the ones related to natural events) from 1900 until the present that meet *at least one* of the following criteria: (i) 10 or more people dead; (ii) 100 or more people affected; (iii) the declaration of a state of emergency; or (iv) a call for international assistance. For more information, see: https://www.emdat.be/frequently-asked-questions

[19] For a full list of administrative levels worldwide, see: https://en.wikipedia.org/wiki/List_of_administrative_divisions_by_country

[20] Moreover, this filtering choice has also been made after discussion with relevant academics in the field.

relatively small, we focussed our attention only on natural disasters at the first or second administrative level for our empirical tests. For completeness, as suggested in Rosvold & Buhaug (2021), we rescaled the more granular polygons provided in GDIS to obtain less disaggregated administrative units for a specific natural disaster. Thus, we obtain polygons for the first-administrative units from GADM if only the second administrative unit polygons are provided in GDIS. Moreover, we obtain first and second-administrative polygons from GADM if only the third administrative unit polygons are provided in GDIS.

Our main measure of *material* exposure to natural disasters is a dummy variable, $D_{i,t}^{Impacted}$, which equals one if at least one of firm locations is in an area affected by a natural disaster and zero otherwise. Throughout the paper, we create further specifications of the $D_{i,t}^{Impacted}$ variable, focussing our attention on the granularity of the natural disaster impact (i.e., first or second administrative level), as well the type of firm location hit by the natural hazard (i.e., either the parent's headquarter, one of its subsidiaries, or both). Figure 1, Panel B, shows a heatmap of UK firm locations exposed to natural disasters at the first administrative level worldwide. We grouped the first administrative units worldwide into four quantiles according to the number of UK companies hit by a natural disaster in that area during the entire sample period. Notably, Figure 1, Panel B, also suggests the relevance of identifying natural disaster exposure at a more granular level when working with international samples. In fact, apart from England and Scotland, other relevant first administrative units worldwide that affected a high percentage of UK firms in our sample are California, Texas, and New York in the United States, as well as Île-de-France in France, or New South Wales in Australia.

5. Physical Climate Risk and Proactive Text Measures

5.1 Building the Physical Climate Risk and Adaptation Measures

Our goal in this study is to construct firm-level proxies for exposure and adaptation to physical climate risks. A fundamental point for researchers employing textual sources to analyse climate risks is related to the text mining procedure to use to construct the text measures. Thus far, the text mining techniques that have been employed in climate finance can be classified into two broad categories: (i) dictionary-based approaches (Engle et al., 2020; Li et al., 2022; Nagar & Schoenfeld, 2022), and (ii) machine learning approaches (Sautner et al., 2022). In this paper, we follow the former approach, which, in our view, can balance two important dimensions. The first is related to the possibility of manually supervising climate change-related terms that may appear out of context in a generic UK annual report. As we explain shortly, we operationalize the possibility to reduce the number of false positives using climate risk n-grams (Li et al., 2022) rather than unigrams (Nagar & Schoenfeld, 2022). In fact, as Loughran & McDonald (2016) noted, financial researchers should be particularly careful when utilising a dictionary approach because '(…) the use of word lists derived outside the context of business applications has the potential for errors that are not simply noise and can serve as unintended measures of industry, firm, or time period'. The second reason to use a dictionary-based approach, as explained in Section 4.1, is related to the not standardized structure of UK annual reports. This feature would make extremely difficult to apply machine learning techniques at a scalable level for large samples of textual data.

We addressed the first goal of constructing a lexicon with relevant physical climate risk terms in two steps. First, we retrieved natural disaster keywords provided from the SENDAI Framework for Disaster Risk Reduction and the IRDR Peril Classification and Hazard

Glossary.[21] As in Li et al. (2022), we enriched these lists from sources including meteorology books and Wikipedia lists. Second, for each unigram, we manually classified the top 3,000 associated bigrams appearing in the annual reports to reduce the possibility of counting false positives. If the top 3,000 associated bigrams were unequivocally used by the management in the context of climate-related topics, we included the corresponding unigrams in the final lexicon. Otherwise, we included the top 3,000 associated bigrams in the physical climate lexicon. The final dictionary consists of 21 unigrams and 658 bigrams. Our first textual measure of physical climate risk is the number of occurrences of unigrams and bigrams related to natural hazards divided by the total number of words in an annual report.

We rely on a dictionary-based approach also to identify firm adaptation strategies to physical climate risks. In this paper, we refer to climate adaptation at the firm level as any action implemented by management to deal with actual or expected physical climate risks and their effects (Goldstein et al. (2018); IPCC (2014)). Differently from the construction of the physical climate risk lexicon, the identification of specific words related to firm-level adaptation strategies is far more elusive and challenging. For instance, Goldstein et al. (2018) identified 1,630 different companies' adaptation strategies by analysing CDP data. However, following our definition above, adaptation may also refer to simpler risk management practices adopted by firms. In fact, a recent survey from S&P Global 100 companies found that 77% of them frame their climate adaptation strategy considering their usual risk management or business continuity plans (C2ES, 2013). The anecdotal evidence provided from these two examples implies that the construction of a climate adaptation lexicon at the firm level should consider a methodology general enough to simultaneously capture both complex and simple risk management practices.

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

To capture this multidimensionality in firm adaptation strategies, we followed an approach similar to that described by Li et al. (2022).[22] Specifically, we identify firm adaptation strategies to physical climate risks using *verbs* denoting a firm's willingness to manage its natural disaster exposure. We constructed such a dictionary by following these steps. First, we analysed all verbs appearing in the proximity of (i.e., previous, same, or next) sentences containing terms in the physical climate dictionary across annual reports. Second, we retained a list of 30 verbs to identify firms' responses to physical climate risks.[23] Our first proxy of firm's adaptation to climate risks is a ratio, *climate proactive ratio*, which is the ratio between the frequency of mentions of the unigrams or bigrams related to the physical climate discussion in the proximity of proactive verbs, scaled by the total number of physical risk terms in an annual report. However, to foster the econometric interpretation of our asset pricing tests, we use the *climate proactive ratio* to define a firm as proactive in a certain year by means of a dummy, $D_{i,t}^{Proactive}$. This dummy variable was constructed using four specifications. Specifically, $D_{i,t}^{Proactive}$ can take the value of one if, in a certain year, the *climate proactive ratio* for a generic firm is: i) greater than zero; ii) greater than 0.5; iii) greater than the median of the distribution of positive physical climate risk ratios in a certain year; iv) greater than the median of the distribution of positive proactive ratios in a certain year.

5.2 Properties of the Physical climate Risk and Proactive Measures

In this section, we provide preliminary evidence of the properties of our text measures. We first focus on the time-series properties of the physical climate risk and climate adaptation measures. Figure 3.A plots the averages of the two text measures over time. As can be observed

[22] Differently from our paper, Li et al. (2022) analyse corporate responses to transition climate risk. The focus of our paper, however, is about corporate strategies toward physical climate risks.
[23] These verbs are: *alleviate, allow, analyse, commence, comply, determine, develop, embed, employ, establish, examine, expand, exploit, implement, initiate, keep, offset, participate, prepare, prevent, prove, reallocate, rehabilitate, repair, replace, require, transform, underpin, upgrade, verify.*

from the figure, both measures have spikes in similar years, suggesting that high climate risk is associated with the need of high climate adaptation. In fact, the correlation between the two physical risk measures is about 0.28, suggesting that the two are somewhat related.

We then move to the analysis of industry relevant patterns. Figure 3.B plots the averages of the two measures by industry. Coherently with previous evidence shown in the literature, companies in the utility industry are the ones disclosing more about physical climate risks (Liu et al., 2022). Interestingly, Figure 3.B also shows that there is greater within industry variation in how firms in this industry disclose about their climate adaptation strategies. Other industries with the highest level of physical climate risk are consumer staples (that embeds companies operating in the food, beverage and tobacco), basic materials, and energy companies. Differently from the utility sector, we notice a more similar level in the disclosure of climate risk and adaptation strategies.

Finally, we report in Table 2 excerpts of annual reports containing disclosure related to climate physical risk and climate adaptation. Interestingly, Table 2 shows anecdotal evidence that several companies in different industries are exposed to the threats of physical climate risks. In response, firms adopt a series of adaptation strategies in order to manage this kind of exposure.

6. Results

6.1 Climate Risk Disclosure and Material Physical Risk Exposure

A coherent climate physical text measure is expected to capture material physical risk exposure at the firm level. Our first hypothesis predicts that the climate text measure of firms impacted by a natural disaster (the treatment group) should be higher than that of non-impacted firms (the control group). We formalised this possibility using a multivariate regression setting. Specifically, we estimate the following model:

$$TM_{i,t}^{High\ Exposure} = \alpha_i + \beta_1 D_{i,t}^{Impacted} + \gamma X_{i,t} + \theta_i + \vartheta_t + e_{i,t} \quad \textbf{(1)}$$

where $TM_{i,t}^{High\ Exposure}$ is our climate risk text mining measure. $D_{i,t}^{Impacted}$ is a dummy variable that takes the value of one if a firm location is affected by a natural disaster during the fiscal-year period t. $\boldsymbol{X_{i,t}}$ is the same vector of control variables used by Li et al. (2022). As physical climate risk varies across firms and time, we include both firm fixed effects (θ_j) and year fixed effects (ϑ_t). Standard errors are estimated conservatively, with standard errors clustered independently at the firm and year levels (Petersen, 2008).

Table 3 shows the results of Eq. (1) when considering worldwide exposure to natural disasters of UK firms. The results in Columns (1) and (2) show that the text measure of firms located in an area affected at the first administrative level worldwide is 0.8% higher than that of non-impacted firms. However, such an identification strategy may be too coarse, as some first administrative areas around the world may be too large to materially affect company operations after a natural disaster. In fact, we show that this difference is more statistically significant (but decreases slightly in magnitude) when we focus on firm locations impacted at the second administrative level. In particular, Columns (3) and (4) show that the text measure of firms located in an area affected at the second administrative level worldwide is significantly 0.7% higher than that of non-impacted firms.

Table 4 shows the results of Eq. (1) when considering only domestic (i.e., UK level) exposure to physical climate risks and our text measure.[24] Importantly, in Table 4 we further consider different specifications of the $D_{i,t}^{Impacted}$ dummy in eq. (1) to better identify the specific

[24] The number of observations in Table 4 decreases with respect to Table 3, as we retain only the years when a natural disaster impacted firms in our sample at the first or second administrative levels in the UK.

type of firm location hit by a natural hazard. Column (1) shows that the text measure of firms located in an area affected at the first administrative level in the UK is 2.3% higher than that of non-impacted firms (t-stat = 2.710). However, we show that this positive association between our text measure and natural disasters is driven by exposure at the headquarters (Column 2), rather than at the subsidiary level (Column 3). We find similar results when we focus on natural hazards at the second administrative level, and, as in Table 4, the magnitude of β_1 in Eq. (1) decreased substantially. Specifically, column (2) shows that the climate text measure of firms with headquarters affected at the first administrative level is 2.2% higher than that of non-impacted firms (t-stat = 3.295). On the other hand, column (5) shows that such a difference is still positive and statistically significant but decreases to 0.8% when considering natural hazards affecting companies' headquarters located at the second administrative level (t-stat = 2.347).

Overall, we interpret the combined evidence in Tables 3 and 4 considering the proprietary costs associated with climate change disclosure (Ilhan et al. 2021). On the one hand, it may be the case that disclosing information about natural disaster impacts at specific firm locations could reveal proprietary information about companies' operations to the general public. This is particularly true when subsidiaries or more granular natural disaster hazards are analysed. However, it may be challenging for a parent firm to disguise climate risk disclosure in its annual report when natural disasters occur at a location known from its stockholder.

6.2 Event Study

To examine the firm value implications of company exposure and adaptation to physical climate risks, we employ an event study methodology. The event study approach has been extensively used in the climate finance literature (for example, Nagar and Schoenfeld, 2022), and it is particularly suitable for testing the hypotheses developed in Section 3. First, it allows us to test the degrees of market perceptions of the impacts of natural disasters on UK firms worldwide and in the UK. Additionally, the event study methodology enables us to examine how investors evaluate the climate risk and adaptation disclosures of impacted firms during these events.

For the event study analysis, we measure the effect of physical climate risk on firm value using cumulative abnormal returns (CAR) around the days of natural disaster realisations. For our asset pricing tests, we retain only those natural disasters that meet each of these criteria. First, to focus on natural hazards likely to elicit higher investor attention, we retain a natural disaster if it is either a storm or a flood. Second, consistent with our estimation window and following Huynh and Xia (2021), we require that the duration of a disaster be less than 30 days.[25] Finally, to find a balance between the number of natural disasters in our sample and actual investor concerns, we keep only natural disasters that caused at least £200 million in damage as reported by EM-DAT (in 2018 CPI-adjusted values). Importantly, for each natural disaster, we broke down our analysis according to whether the geocoded firm locations were impacted at the first or second administrative level.

For our difference-in-difference identification strategy, we classify treatment companies those firms located in a disaster area. For each event, we follow Nagar and Schoenfeld (2022) and compute the cumulative market-adjusted returns for the treatment and control firms over the [-5,+5] period.[26] All returns are adjusted using contemporaneous returns for the FTSE All

[25] After applying the filters explained in this section, the median duration of natural disasters is of four days.
[26] Although Nagar and Schoenfeld (2022) use this estimation window for storms only, we have reasons to believe that it also could be applied to analyse the impacts of floods on firm value. For instance, the Flood Forecasting Centre provides floods forecasts in the UK (on a daily basis) for the next five days. For more information, see: https://check-for-flooding.service.gov.uk/

Share Index. To achieve the first and second goals of the analysis, we estimated the following model:

$$CAR_{i,t}[-5,+5] = \alpha_i + \beta_1 D_{i,t}^{Impacted} + \beta_2 D_{i,t-1}^{High\ Exposure} + \beta_3 D_{i,t}^{Impacted} * D_{i,t-1}^{High\ Exposure} + \gamma \boldsymbol{X_{i,t}} + \theta_i + e_{t,i} \quad \textbf{(2)}$$

where $CAR_{i,t}[-5,+5]$ denotes the cumulative abnormal returns of firm i around natural disaster events. The variable $D_{i,t}^{Impacted}$ is an indicator variable that equals one if a firm's location is in an affected area during the event date. Given the results in Section 6.1, we focus on the impacts at the headquarters or subsidiaries level when analysing natural disasters worldwide. In contrast, we focus only on headquarter level impacts when we analyse domestic exposure of companies in our sample. The variable $D_{i,t-1}^{High\ Exposure}$ takes the value of one if the firm text mining average is greater than the yearly sample average the year before a natural disaster event.[27] The term $\boldsymbol{X_{i,t}}$ is the same vector of control variables used in Nagar and Schoenfeld (2022), and it allow us to control for the characteristics underlying the Fama-French five factors. θ_i represents firm fixed effects, and absorb time-invariant and potentially endogenous firm-level characteristics. Standard errors are estimated conservatively, with standard errors double clustered at the firm and year levels (Petersen, 2008). The coefficient of interest in Eq. (2) to test our second hypothesis is β_3, as it captures the average return differential between impacted firms that have different levels of physical climate risk disclosure.

[27] Differently from Nagar and Schoenfeld (2022), we use the yearly sample *average* rather the *median* sample average to compute $D_{i,t-1}^{High\ Exposure}$. We prefer our approach as the latter construction tends to overclassify firms with high levels of climate risk disclosure. The reason for this is that, throughout the sample, the *median* sample average always equals zero. However, later in this section we show that our main asset pricing results remains unchanged when we use the exact Nagar and Schoenfeld (2022) methodology.

To achieve our third goal of the analysis, we extended Eq. (2) and estimated the following model:

$$CAR_{i,t}[-5,+5] = \alpha_i + \beta_1 D_{i,t}^{Impacted} + \beta_2 D_{i,t-1}^{Not\ Proactive} + \beta_3\, D_{i,t-1}^{Proactive} + \beta_4\, D_{i,t-1}^{Not\ Proactive} * D_{i,t}^{Impacted} + \beta_5\, D_{i,t-1}^{Proactive} * D_{i,t}^{Impacted} + \gamma\, \boldsymbol{X_{i,t}} + \theta_i + e_{t,i.} \qquad \textbf{(3)}$$

The $D_{i,t-1}^{Proactive}$ takes the value of one the year before a natural disaster a company had the first proactive (defined in section 4) that equals one and the $D_{i,t-1}^{High\ Exposure}$ dummy that equals one.[28] By estimating Eq. (3), we can isolate the effect of disclosing physical climate risks in a non-proactive way (via $D_{i,t-1}^{Not\ Proactive}$), and the effect of disclosing physical climate risk in a proactive way (via $D_{i,t-1}^{Proactive}$), taking firms that disclose less than average physical climate risks as a reference group. If firm adaptation to climate change pays off when the effects of climate change materialize, we would expect only β_5 in eq. (3) to be positive and statistically significant. On the other hand, if only the climate disclosure dimension is priced, we would expect only β_4 in eq. (3) to be positive and statistically significant.

Table A2 presents the results of Eq. (2) when analysing equity market responses to both foreign and domestic exposure. The estimated coefficients for β_1 in eq. (2) are essentially similar when we consider natural disaster impacts at the first (Column 1), or second (Columns 4) administrative levels. We find no evidence that market-adjusted returns are lower for firms impacted by natural disasters than for those that are not. In Table A3, we construct additional measures for a firm's exposure to natural disasters to test the robustness of these findings. Following Huynh & Xia (2021), we use economic damage information about natural disasters and compute a firm-level exposure, $Ln(Damage)_{i,t}$, as the location-weighted average of economic damages across the specific administrative levels where the firm locations are

[28] In Section 6.3, we conduct robustness tests estimating eq. (3) with the other proactive dummies defined in Section 5. As we show in that section, regression results corroborate the main outcomes that we discuss here.

located, using firm locations total assets, sales or employment as weights. Table A3 presents the results. Consistent with the results in Table A2, we do not find any association between natural disaster exposure and the market-adjusted returns of impacted firms.[29] Finally, Table A2 shows that we do not find any relationship between climate or adaptation disclosures and firm value. This evidence suggests that investors' concerns about natural disaster impacts could be a sufficient condition for the relationship between climate disclosure and firm value. Moreover, future research can revisit other settings to analyse whether our insignificant results arise from low investor concerns for foreign exposure to natural disasters of UK firms, or low investor consciousness of UK firms' corporate structure worldwide. Given that Table 4 shows that UK companies disclose their international exposure to natural disasters to some extent, future research in climate finance may test whether an equity market response arises during the publication dates of companies' annual reports.

Previous results are starkly different when we focus on domestic natural disaster exposure. Table 5 presents the results. Notably, Table 5 shows that the magnitude and statistical significance of the results strictly depend on the granularity of domestic impacts (and, thus, treated firms). Specifically, while in column (1) the sign of β_1 in Eq. (2) is negative but statistically insignificant (t-value = -0.053), in column (4) we find that firms affected at the second administrative level exhibited a lower market-adjusted return of about 200 bps relative to unaffected firms (t-value = -4.705). This effect is nearly four times larger than that identified by Nagar and Schoenfeld (2022), who analysed equity market responses for US firms headquartered in the state (i.e., first administrative level in the US) hit by a natural disaster. To

[29] As explained in Huynh and Xia (2021), although the measure $Ln(Damage)_{i,t}$ may be compelling, a caveat in this measure is that it could take time for national authorities to provide estimates of the economic damages arising after a natural disaster. In contrast, the $D_{i,t}^{Impacted}$ variable does not suffer the same concern, as natural disasters (such as floods or storms) are reported in the media in a timely manner (Engle et al., 2020).

the best of our knowledge, we are not aware of any prior study documenting the impact of natural disasters on the equity-adjusted returns of a large cross-section of UK listed firms.

To test our second hypothesis, in Table 5 we further control for the effects of climate disclosure on firm value. If climate risk disclosure harms firm value when the effects of climate change are material, we would expect β_3 in Eq. (2) to be negative. In contrast, if investors positively evaluate climate risk disclosure in times of higher uncertainty, β_3 in Eq. (2) should be positive and significant. In column (5) we find that β_3 is positive and statistically significant (t-value = 2.121). The estimate indicates that high disclosing firms impacted from a natural disaster suffer a lower loss in value, as their market adjusted returns recover from the -220 bps to -100 bps, after summing over the coefficient estimates. We repeat the estimation in column (5) constructing the $D_{i,t-1}^{High\ Exposure}$ variable as in Nagar and Schoenfeld (2022). In un-tabulated results, the estimated coefficient for β_3 remains positive and statistically significant (t-value = 2.203). Importantly, the results explained so far cannot be driven from differences in size, value, profitability, or physical asset investments between firms, as these factors are included as control variables. Moreover, controlling for firm fixed effects further excludes the fact that our firm value estimates are driven from companies' time-invariant exposure to natural disasters.

To test our third hypothesis, we further break down the $D_{i,t-1}^{High\ Exposure}$ variable to grasp whether the positive association between climate disclosure and firm value is driven from firms that disclose climate adaptation strategies in their annual reports. Table 5, column (6) reports the results.[30] Contrary to the above expectation, column (6) shows that impacted firms *not* disclosing climate adaptation strategies suffered a significant lower loss in value of 170 bps compared to not disclosing firms (t-value = 4.084). In contrast, impacted firms disclosing climate adaptation strategies were not rewarded in the same manner. Specifically, column (6)

[30] Under these settings, impacted firms with low levels of climate risk disclosure serve as base category.

shows that impacted firms disclosing climate adaptation strategies exhibited a higher loss in value of 20 bps compared to not disclosing firms, although this estimate is not statistically significant (t-value = -0.178). In Table A4, we report further specifications of Eq. (3), considering all the different climate adaptation measures (as defined in Section 5). Overall, results in Table A4 confirm the main findings of column (6) in Table 5. In other words, when the effects of climate change materialise, investors positively reward only firm transparency to physical climate risks, and not also firm efforts to address them.

6.3 Robustness Tests

The first potential concern with our results is whether the TWFE approach we use to estimate Eqs. (2) and (3) is appropriate for our staggered DID design. A recent literature in micro-econometrics warns against the possibility that the TWFE estimator could result in Type-I and Type-II errors under specific scenarios (Baker et al., 2022; Goodman-Bacon, 2022). Baker et al. (2022) reviewed this literature, analysing specific examples in the corporate finance area. However, the concerns advanced in Baker et al. (2022) mainly referred to staggered DID settings involving *policy changes* (i.e., man-made shocks), and no other types of exogenous events such as natural disasters. This point is important, as natural disasters are generally known to provide greater amount of exogenous variation than man-made shocks (Rehse et al., 2019). To further confirm this point and address the validity of the TWFE approach in our setting, it is important to remember that the crucial assumption underlying TWFE is the parallel trend assumption. In other words, treatment firms would have seen similar trends in their market adjusted returns relative to control firms in the absence of the treatment. We apply two placebo tests similar to the ones applied by Nagar and Schoenfeld (2022). Specifically, we assign to each natural disaster event two placebo dates, one that is 30 calendar days before its true date, and the other 30 calendar days after the true date. Table A5 presents the estimates. For both tests, we do not find any statistically significant result. Although the parallel trend assumption is never verifiable, these placebo tests mitigate the possibility that results in Table 5 are driven by endogenous concerns and confirm that the TWFE is an appropriate estimator in our setting.

The second potential concern with our results in Table 5 is that they might be driven by the specific verbs we choose to identify firm strategies against natural disaster exposure. We therefore run a test to show that the above results are robust regardless of the specific type or number of verbs we use when estimating Eq. (3). Specifically, we created 1,000 combinations to build the climate adaptation measure considering two different options. First, we constructed the climate adaptation measures considering 30, 40 or 50 climate adaptation verbs selected randomly from a list of 180 verbs introduced in Section 5. With respect to the second option, we constructed the proactive measures considering: 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. To make this exercise as random as possible, the random choices we listed above are *not* mutually exclusive. In other words, for every trial we ran, there is a *combination* of different values that each random option can assume.[31] Table A6 shows the percentages of significant beta coefficients in Eq. (3) over the 1,000 combinations. In Table A6, we further report the results considering all the four different proxies of firm adaptation described in Section 5. We deem a beta significant if it is at least significant at the 5% level. Consistent with the results in Table 5, the coefficient β_4 in eq. (3) is statistically significant 88% of the times across the four combinations. This percentage decrease to 14.14% when one considers the coefficient β_5 in Eq. (3). This test confirms the more general result that investors

[31] For instance, a specific combination may imply the construction of a proactive measure with 40 verbs that appear in the same or following sentence containing terms in our physical climate risk dictionary.

do not price positively climate adaptation disclosure, especially when firms are impacted by a natural disaster. In the following section, we provide an explanation for this counterintuitive result.

A third potential concern is that the results in Table 5 might be driven by the collinearity between the variables in Eq. (3). To address this concern, we report in Table A7 the correlations between the main regressors in Eq. (3) over the 1,000 combinations described above. As Table A7 shows, the correlations we identify are generally low in absolute value, suggesting that collinearity is not driving the results we observe in Table 5.

7. Alternative Explanations

7.1 Discount Rate or Cash Flow News Hypothesis

The previous section showed that, according to the specific area affected in the UK, natural disasters realisations had firm value implications. Companies disclosing their exposure to physical climate risks attenuated these negative effects, a result in line with the benefits of climate disclosure. In contrast, impacted firms mentioning to adapt to physical climate risks were evaluated on par with not-disclosing firms. The aim of this section is to explain the underlying channels driving these results. In general, a decline in equity returns may be explained by two different underlying channels, namely a cash flow channel or a discount rate channel (Liu et al., 2017). In the following subsections, we analyse each of these possibilities in detail.

7.1.1 Expected Cash Flow Analysis

To analyse our first explanation, we rely on changes in analysts' earnings forecast before and after natural disaster realisations. If investors anticipated a drop in cash flows after a natural disaster event, we would expect to observe a drop in analysts' earnings forecasts, especially for impacted firms disclosing to adapt to physical climate risks. Following Nagar and Schoenfeld (2022), we analyse changes in the mean earnings forecast per share (EPS) between 20 trading days after and 20 trading days before a natural disaster (i.e., one month before and one month after the event). Therefore, we create an indicator variable, $Downgrade_i$, that equals one if, for the fiscal-yearend after a natural disaster, analysts revised downwards their estimate about firms' earnings from one month after the event to one month before, and zero otherwise.[32] We estimated specifications similar to the ones in Eqs. (2) and (3) but replace market adjusted returns with the $Downgrade_i$ variable.

Table 6 presents the results in the first three columns. Hypothesis 4A predicts that the regression coefficients for β_1 and β_5 in Eqs. (3) are negative and statistically significant. However, we do not find significant evidence of analysts revising downwards their EPS estimates neither for firms impacted from a disaster nor for climate-adaptive disclosing firms. Overall, these results tend to reject Hypothesis 4A (i.e., the cash flow hypothesis).

7.1.2 Stock Return Volatility Analysis

Another possible explanation underlying the results we observe in Table 6 may be due to an increase in the market price of risk brought from natural disaster realisations. If this is the case, we would expect stock return *volatility* to increase over the same period, especially for more

[32] We considered the fiscal-year end and not the subsequent quarter as in Nagar and Schoenfeld (2022) given the low coverage of analysts' data in IBES at the quarter level for our sample.

proactive firms. We test change in volatility as stated in Hypothesis 4B following the methodology described in Liu et al. (2017). Specifically, we computed a measure of abnormal volatility by measuring the change in volatility from before to after a natural disaster in percentage (ΔVol_i). As in Liu et al. (2017), we use daily stock returns to construct volatility. We use one month as the post natural disaster period. Due to seasonality, the pre natural disaster period is defined as the same calendar time window as in the previous year (Liu et al., 2017). To test Hypothesis 4B, we estimate specifications similar to the ones in Eqs. (2) and (3) but replace market adjusted returns with the ΔVol_i variable.

Table 6 presents the results in the last three columns. Hypothesis 4B predicts that the regression coefficients for β_1 and β_5 in Eqs. (3) are positive and significant. However, any of these betas is statistically significant in Table 6. In other words, this result indicates that we cannot detect any significant simultaneous increase in risk neither for impacted nor for adaptive disclosing firms. Overall, these results reject Hypothesis 4B (i.e., the discount rate hypothesis based on the risk story).

7.1.3 Stock Liquidity Analysis

We finally explore possible explanations based on the relationship between firm value and ambiguity posited in prior studies (Rehse et al., 2019). In particular, Rehse et al. (2019) showed that during times of higher ambiguity in the equity market, stock liquidity tends to be lower. Given that ambiguity aversion is priced in the cross-section of stock returns (Brenner and Izhakian, 2018), a decrease in liquidity after a natural disaster would be coherent with a higher risk premium required by investors for impacted firms. Following Rehse et al. (2019), we use two measures of stock liquidity, namely British-pounds trading volume and bid-ask spreads (both at the daily frequencies). Moreover, as in Rehse et al. (2019), we compute daily bid-ask spreads following the approach proposed by Chung and Zhang (2014). In order to better discern the ambiguity from the risk-based explanation, we construct measures of abnormal volume and bid ask spreads similar to the one described in section 7.1.2 for abnormal volatility. Moreover, given that the literature show that risk is an important determinant of trading volume and bid ask spreads, we further control for abnormal volatility when testing the relationship between natural disaster and liquidity. This methodology allows us to control for additional potential sources of confounding variation between stock liquidity and uncertainty.

Table 7 reports the estimates. The results show that mean closing spreads increased significantly for firms impacted from a natural disaster. Column (1) shows a significant positive coefficient for $D_{i,t}^{Impacted}$ of 0.164% (t-value = 2.227). On the other hand, column (2) shows that the firms with higher levels of physical climate risk disclosure suffered a lower increase in closing spreads, as the estimate for $D_{i,t-1}^{High\ Exposure}$ is of -0.084% (t-value = -2.571). Interestingly, when we break down the $D_{i,t-1}^{High\ Exposure}$ variable, in column (3) we find that this negative association between closing spreads and disclosure is not driven by firms disclosing climate adaptation. Specifically, column (3) shows that firms *not* disclosing climate adaptation strategies suffered a significant lower increase in closing spreads of -0.123% compared to not disclosing firms (t-value = -3.001). We find similar results about liquidity dynamics for trading volume. Column (4) shows that trading volume decreased of -1.178% for impacted firms (t-value = -2.689). Furthermore, column (5) shows that disclosing firms exhibited a significant increase in trading volume, and column (6) shows that this lower drop in volume is driven by firms not disclosing adaptation strategies in their annual reports. In sum, regression results are coherent with the idea that the negative returns in Table 5 are driven from a higher ambiguity about firm valuations due to natural disasters. These results also show that while general disclosure of physical risks in annual reports can decrease this ambiguity, the same does not hold for climate adaptation disclosure. In particular, this kind of disclosure seem to generate uncertainty in investors' evaluation, on par with firms that do not disclose their natural hazard exposure in their annual reports.

7.2 Sustainability Compliance

Another possibility underlying the results we observe may be due to firms that do not "walk the talk" when mentioning their proactiveness toward physical climate risks in the annual reports (Raghunandan & Rajgopal, 2020). The reason to appear "climate-proof" to investors may denote firm's willingness to divert attention from other sustainability issues that may be value relevant to their shareholders (Huynh & Xia, 2021). However, if investors grasp these kinds of greenwashing strategies, then one would not expect proactive firms to be rewarded from the market, especially when hit by a natural disaster.

To empirically show this, we gathered data from the Violation Tracker UK database, compiled by the non-profit organization Good Jobs First. Violation Tracker UK provides data from 2010 to 2020 about enforcement actions brought against more than 77,000 companies by 49 government regulators settled in England, Scotland, Wales and Northern Ireland. Violation Tracker UK classifies the types of offences in the following groups: (i) safety-related offences; (ii) environment-related offences; (iii) employment-related offences; (iv) financial offences; (v) competition-related offences and (vi) consumer-protection-related offences. The dataset provides a unique "ISIN" identifier for the parent, if present, of sanctioned companies. However, given that these companies may have multiple parents, we accounted for this by merging our corporate structure dataset with the information provided in Violation Tracker UK. The final merged dataset contains 307 UK listed parent companies (with respect to the initial 141 unique parents initially provided from Violation Tracker UK).

To formalise the possibility that firms disclosing climate adaptation strategies are more likely to incur in sustainable-related violations, we estimated the following PROBIT model:

$$D_{i,t+1}^{Proactive} = \alpha_i + \beta_1 TM_{i,t}^{High\ Exposure} + \beta_2 Violation_{i,t} + \beta_3 X_{i,t} + \theta_j + \vartheta_t + e_{t,i} \qquad (4)$$

where $D_{i,t+1}^{Proactive}$ is the first climate adaptation dummy variables defined in Section 5. $Violation_{i,t}$ can assume two different specifications. It could be either a dummy variable, $\boldsymbol{D_{i,t}^{Violation}}$, that takes the value of one if a firm committed at least one violation in year t. Alternatively, it could represent the log of the total amount (in £) of sanctions incurred by a firm in year t. We considered three different settings when building the $Violation_{i,t}$ variable in Eq. (6). Specifically, we consider: (i) all types of violations provided in the Violation Tracker UK database.; (ii) only safety and environmental-related violations; or (iii) environmental-related violations only to build the $Violation_{i,t}$ variable in eq. (4). $TM_{i,t}^{High\ Exposure}$ is the normalised value of our physical climate risk ratio measure. $\boldsymbol{X_{i,t}}$ is a set of control variables. θ_j are industry fixed effects, while ϑ_t are year fixed effects. Standard errors are double clustered at the firm and year level.

Table 8 shows the results. Regardless of the type of violation analysed, we find that sanctioned firms in a certain year are not more likely of disclosing climate adaptation strategies the year after. Moreover, if anything, we can observe that in some cases the coefficients on the $Violation_{i,t}$ variable in eq. (4) are *negative* (although not statistically significant). Overall, these results may be coherent with the so called "*greenhush*" hypothesis (Ginder et al., 2021). In other words, firms disclosing climate adaptation do not withhold strategic information about their environmental and social actions. In turn, climate adaptation disclosure thus increases the likelihood for firm of being targeted by climate activists and regulators. As a result, this may push climate proactive firms to pay more attention to avoid being involved in environmental, safety or sustainable-related penalties more in general.

8. Conclusions

The stochastic evolution of near and long-term risks associated with climate change will likely require firms to reshape a large number of their strategic operations. The way in which companies will manage to adapt to climate risks will dictate losers and winners from climate change in the coming decades. In this paper, we develop a large-scale measure of individual firm exposure and adaptation to physical climate risks. Validation tests show that our measure can capture foreign and domestic exposure to natural disaster.

Asset pricing tests show that natural disasters have a negative impact on firm value, especially domestic rather than foreign events. We document that impacted firms disclosing their exposure to physical climate risks were rewarded from the market, a result in line with the benefits associated with climate change disclosure. However, firms impacted from natural disasters mentioning to act in a more proactive way to deal with physical climate risks were not rewarded in the same manner and evaluated on par with not-disclosing firms. We explain these results showing that the negative value effects are mainly driven by a change in discount rates around natural disaster events, rather than an anticipation of a decline in firm cash flows or greenwashing practices. Importantly, the main outcome of this paper is that climate adaptation disclosure seem to induce uncertainty in investor evaluation.

Our results have important implications for policies aimed at fostering the generalised disclosure of climate adaptation practices in companies' annual reports. As explained in Section 2, several governments worldwide are introducing guidelines for firms in order to increase climate adaptation disclosure in companies' annual reports. Our study thus warns regulators about the possible market reactions that these guidelines may trigger in financial markets. However, we see various relevant avenues for further research on the effects of climate adaptation disclosure on uncertainty in different regulatory regimes. Specifically, it would be interesting to analyse our whether our results also hold in other financial markets where disclosure of physical climate risk is regulated in a more binding way. Such evidence would shed light on the more generalized between climate adaptation disclosure and firm value.

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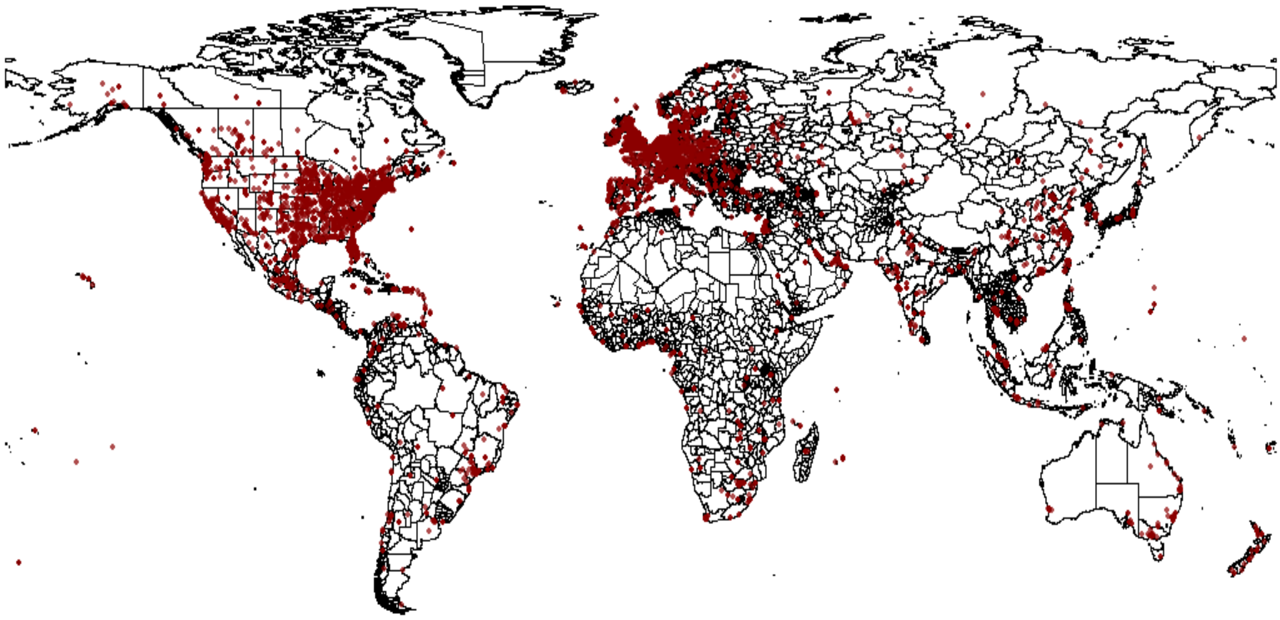
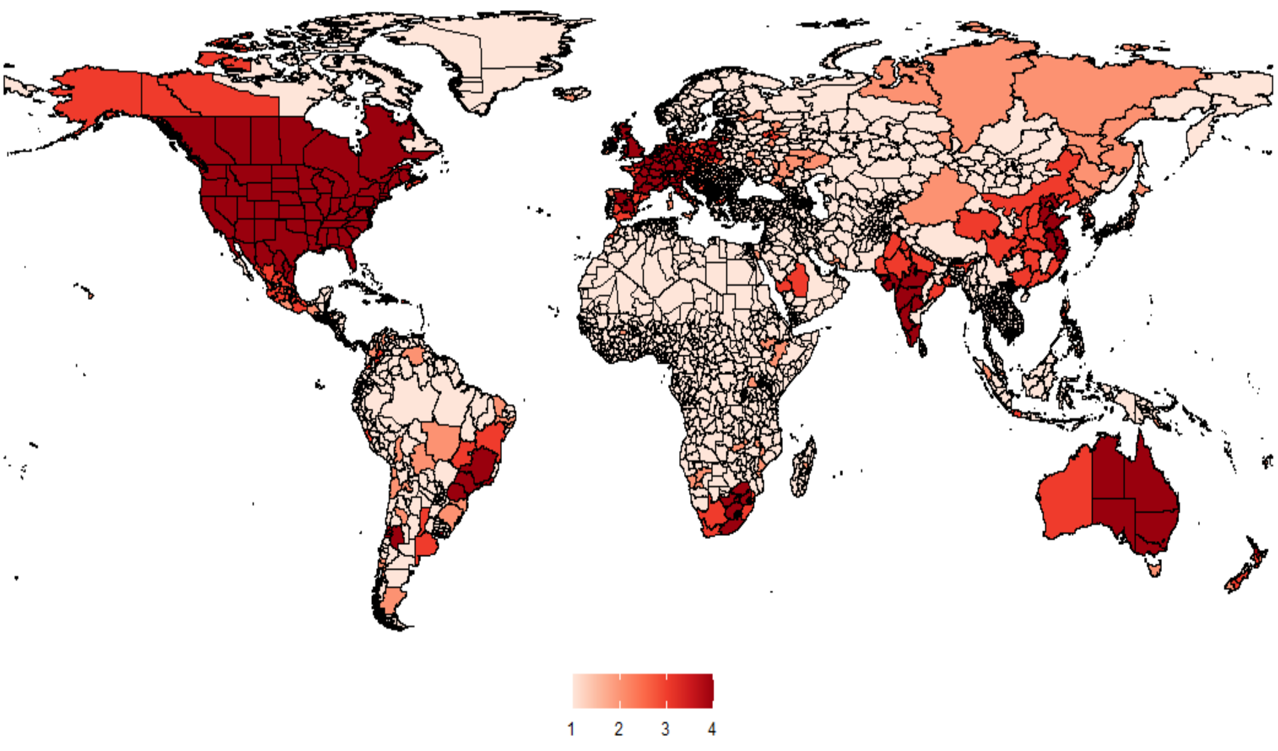
Figure 1. Geographic Location and Exposure of UK Firms Headquarters and their Subsidiaries Worldwide*.* *This figure shows the worldwide geographical distribution and exposure to natural disasters of UK firms in our sample. Panel A shows the location of UK parents' headquarters (in the UK) and their subsidiaries (in the UK or worldwide). Corporate ownership relationships are obtained from FAME, while firm locations data are obtained from FAME, Dun & Bradstreet. and country-specific news websites. Panel B exhibits countries where most of UK parent firms were exposed to natural disasters either via their headquarters or their subsidiaries. We group countries into four quantiles according to the number of natural disasters that impacted UK parent companies during the whole sample period. In this figure, a firm location is considered exposed if its first administrative division level worldwide was hit by a natural disaster that costs at least £10 million in 2020 constant pounds. Natural disaster data are obtained from GDIS.*

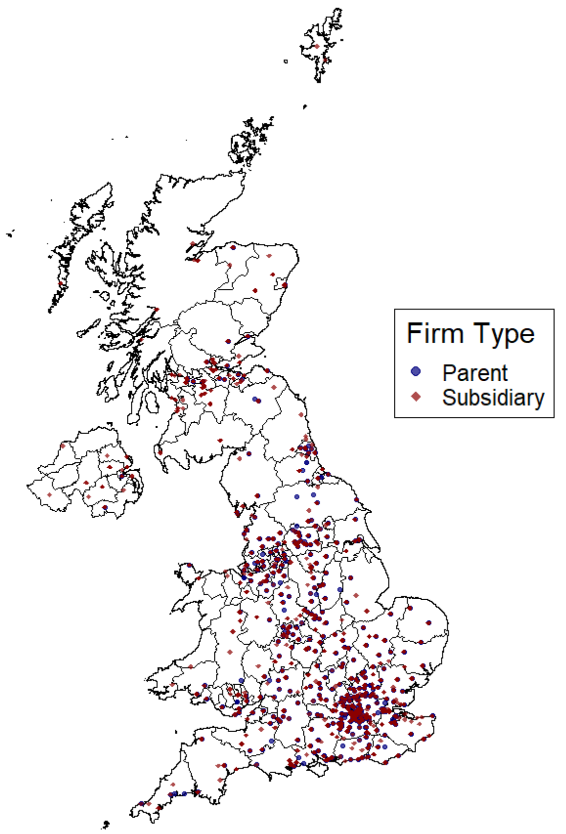


a) Panel A: *Geographic Location of UK Firms' Headquarters and their Subsidiaries*

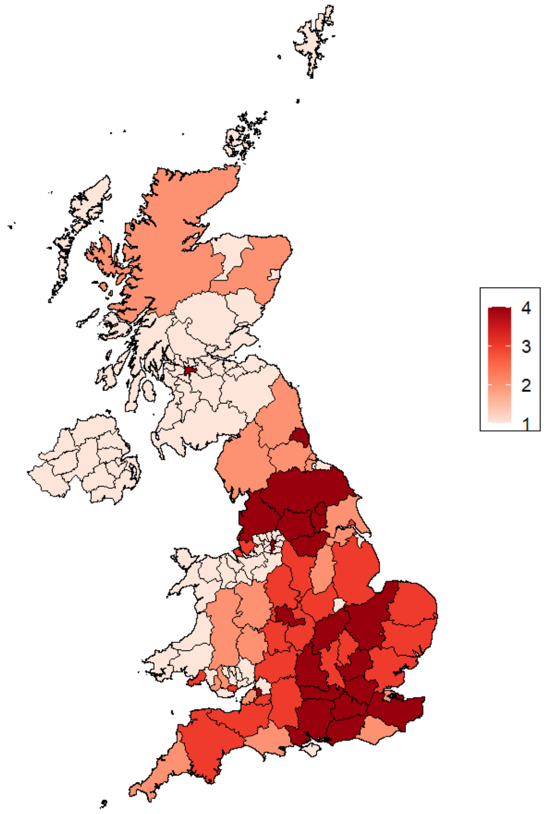


b) Panel B: *Geographic Exposure of UK Firms' Headquarters and their Subsidiaries*

***Figure 2. Geographic Location and Exposure of UK Firms Headquarters and their Subsidiaries in the UK**. This figure shows the UK 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 are obtained from FAME, while firm locations data are obtained from FAME, Dun & Bradstreet, and country-specific news websites. Panel B exhibits countries where most of UK parent firms were exposed to natural disasters either via their headquarters or their subsidiaries. We group countries into four quantiles according to the number of natural disasters that impacted UK parent companies during the whole sample period. In this figure, a firm location is considered exposed if its first administrative division level worldwide was hit by a natural disaster that costs at least £10 million in 2018 constant pounds. Natural disaster data are obtained from GDIS.*

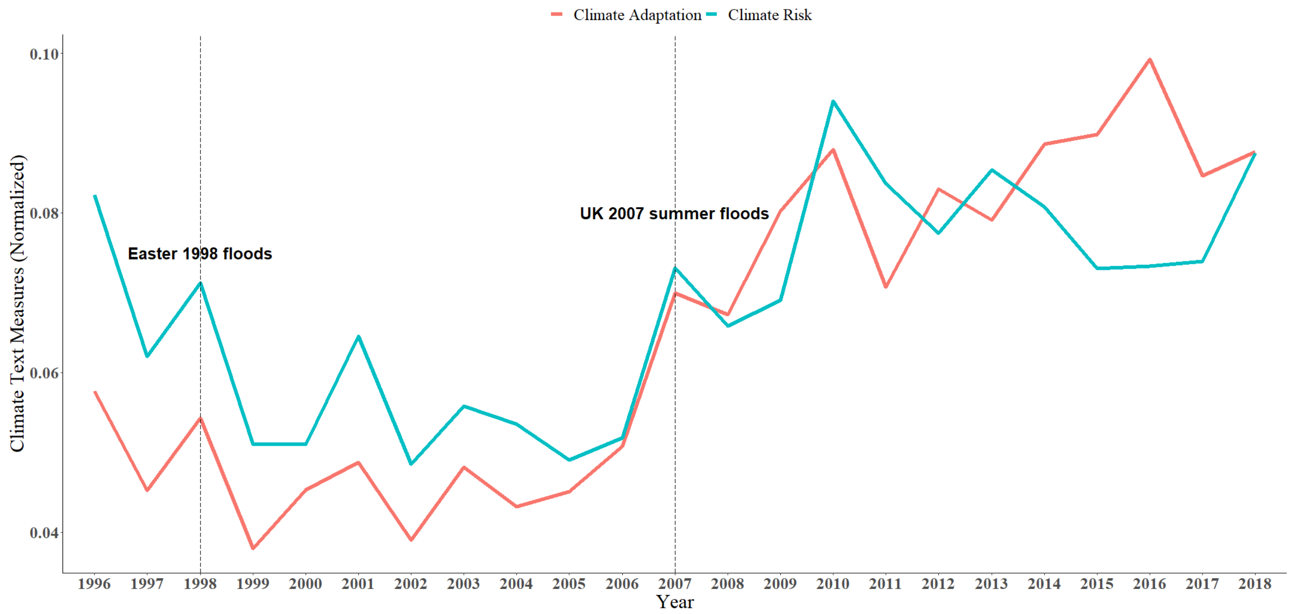


***a) Panel A:** Geographic Location of UK Firms' Headquarters and their Subsidiaries*

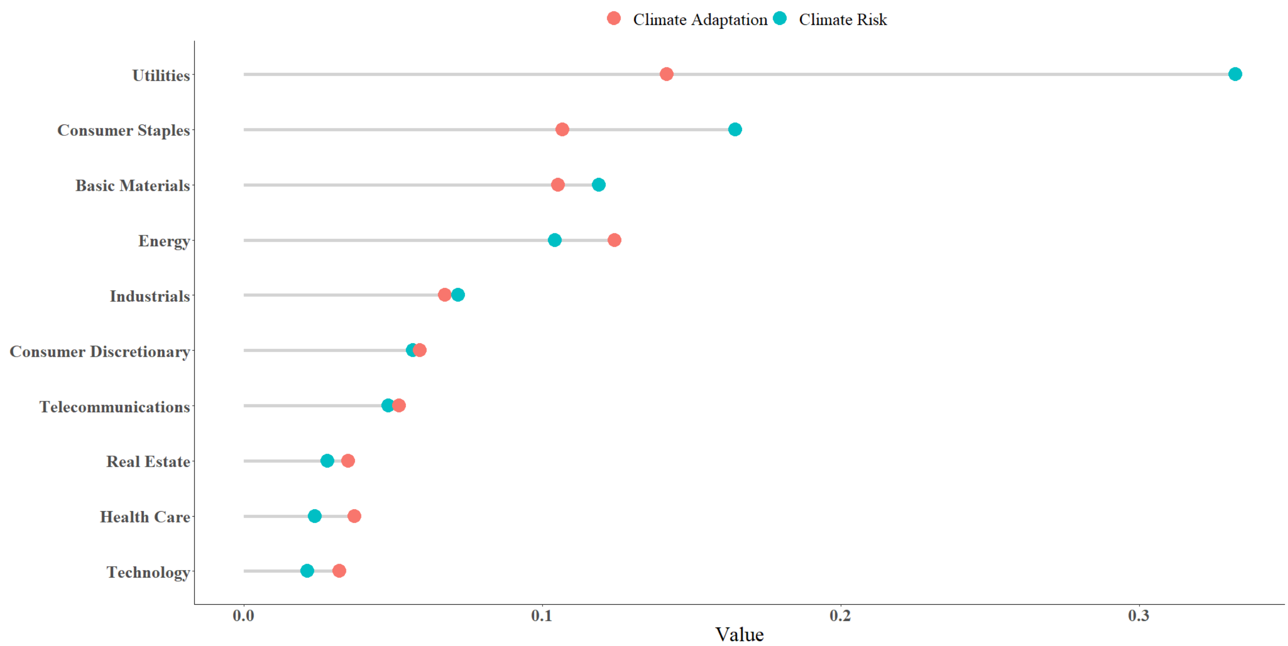


***b) Panel B:** Geographic Exposure of UK Firms' Headquarters and their Subsidiaries*

Figure 3. Properties of the Physical climate Risk Measures. *These figures report the average of our and the Nagar and Schoenfeld (2022) across two different dimensions. Panel A show the time-averages of the two measures, while Panel B plots the averages of the physical risk measure by industry. We use the ICB classification system to gather information about company affiliation.*



Panel A) Time-series patterns of the physical climate text measures



Panel B) Industry patterns of the physical climate text measures

Tables

Table 1. Summary Statistics. *This table reports the summary statistics for the variables used in the paper. We obtain accounting data from Worldscope, FAME and Compustat Global. Our initial sample includes all nonfinancial firms listed on the London Stock Exchange from 1996 to 2020. All variables are defined in Appendix A1. All continuous variables are winsorized at the 1% level.*

	N	Mean	SD	P25	P50	P75
Log(TA)	22,542	11.173	2.187	9.682	11.001	12.532
PPE	22,542	0.265	0.256	0.052	0.182	0.406
B/M	22,542	0.679	0.783	0.255	0.508	0.947
ROA	22,542	-0.055	0.328	-0.043	0.035	0.079
CapEx	22,542	0.049	0.057	0.012	0.03	0.064
Leverage	22,542	0.192	0.207	0.018	0.148	0.289
$TM_{i,t}^{High\ Exposure}$	22,542	0.061	0.155	0	0	0.045
$TM_{i,t}^{NS}$	22,542	0.053	0.166	0	0	0
Proactive Ratio	22,542	0.052	0.182	0	0	0
$D_{i,t}^{Proactive\ (I)}$	22,542	0.110	0.313	0	0	0
$D_{i,t}^{Proactive\ (II)}$	22,542	0.033	0.18	0	0	0
$D_{i,t}^{Proactive\ (III)}$	22,542	0.138	0.344	0	0	0
$D_{i,t}^{Proactive\ (IV)}$	22,542	0.055	0.228	0	0	0
$D_{i,t}^{Impacted\ (World,\ ADL1)}$	22,542	0.331	0.470	0.000	0.000	1.000
$D_{i,t}^{Impacted\ (World,\ ADL2)}$	22,542	0.350	0.355	0.000	0.000	0.000
$D_{i,t}^{Impacted\ (UK,\ ADL1)}$	22,542	0.697	0.460	0.000	1.000	1.000
$D_{i,t}^{Impacted\ (UK,\ ADL2)}$	22,542	0.133	0.339	0.000	0.000	0.000

Table 2. Excerpts in UK Annual Reports containing climate physical and climate adaptation disclosure. *The table presents the excerpts in UK annual reports containing sentences related to climate physical and climate adaptation disclosure. We also report the fiscal year in which an annual report was issued, as well as the industry affiliation of the firm.*

Firm	Fiscal Year	Industry	Text surrounding keywords
Anglo American plc	2015	Basic Materials	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.
Essentra PLC	2011	Technology	The aim of the planting was to increase the number of mangrove forested areas to maintain the balance of the mangrove ecosystems which provide a habitat to many marine animals and help to prevent coastal erosion reducing damage from storm surges as well as acting as a natural water filter.
R.E.A Holdings PLC	2015	Consumer Staples	Responsible agricultural practices the onset of el nino conditions in borneo during the last quarter of 2015 resulted in the groups operations being subject to several months of drought emphasised the importance of implementing responsible agricultural practices.
Cairn Energy PLC	2016	Energy	This led us to examine our portfolio resilience in 2015 an exercise we revisited in 2016 using different climate scenarios including limiting global temperature rise to well below 2c see below.

Table 3. Multivariate tests for the firms' climate risk measure (Worldwide Exposure). *This table examines whether natural disaster realizations worldwide affected the physical climate risk text measure of impacted firms relative to not impacted firms from 1996 to 2018. In all columns, the dependent variable is our normalized physical climate risk ratio. In all columns, a firm is considered impacted if either its headquarter or one of its subsidiaries is located in an affected area in a given year. In columns (1) and (2), we define an area affected if a natural disaster happened in one of the first-level administrative division worldwide. In columns (3) and (4) we define an area affected if a natural disaster happened in one of the second-level administrative division worldwide. All continuous variables are winsorized at the 1% level. t-statistics are in parentheses and standard errors are double clustered at the firm and year level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.*

Dependent Variable: $TM_{i,t}^{High\ Exposure}$				
Hazard Granularity:	*ADL1*		*ADL2*	
Specification:	(1)	(2)	(3)	(4)
$\boldsymbol{D_{i,t}^{Impacted}}$	**0.008****	**0.008***	**0.007*****	**0.007****
	(2.080)	**(1.893)**	**(2.636)**	**(2.551)**
Log(TA)		0.007***		0.008***
		(3.080)		(3.099)
PPE		0.032**		0.032**
		(2.084)		(2.077)
CapEx		0.029		0.030
		(1.078)		(1.102)
Leverage		-0.004		-0.004
		(-0.492)		(-0.513)
ROA		-0.001		-0.001
		(-0.213)		(-0.265)
Obs.	22,542	22,542	22,542	22,542
R2 Adj.	0.512	0.513	0.512	0.513
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 4. Multivariate tests for the firms' climate risk measure (Domestic Exposure). *This table examines whether natural disaster realizations in UK affected the physical climate risk text measure of impacted firms relative to not impacted firms from 1996 to 2018. In all columns, the dependent variable is our normalized physical climate risk ratio. In columns (1) and (4), a firm is considered impacted if either its headquarter or one of its subsidiaries is located in an affected area in a given year. In columns (2) and (5), a firm is considered impacted if its headquarter is located in an affected area in a given year. In columns (3) and (6), a firm is considered impacted if one of its subsidiaries is located in an affected area in a given year. In columns (1), (2) and (3), we define an area affected if a natural disaster happened in one of the first-level administrative division in the UK. In columns (4), (5) and (6), we define an area affected if a natural disaster happened in one of the second-level administrative division in the UK. All continuous variables are winsorized at the 1% level. t-statistics are in parentheses and standard errors are double clustered at the firm and year level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.*

Dependent Variable: $TM_{i,t}^{High\ Exposure}$						
Hazard Granularity:		*ADL1*			*ADL2*	
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{D_{i,t}^{Impacted}}$	**0.023*** **			**0.008** **		
	(2.710)			**(2.199)**		
$\boldsymbol{D_{i,t}^{Impacted\ (HQ)}}$		**0.022*** **			**0.008** **	
		(3.295)			**(2.347)**	
$\boldsymbol{D_{i,t}^{Impacted\ (Subs.)}}$			**-0.003**			**0.008***
			(-0.561)			**(1.692)**
Log(TA)	0.008***	0.008***	0.008***	0.007**	0.007**	0.007**
	(2.769)	(2.668)	(2.834)	(2.539)	(2.530)	(2.559)
PPE	0.023	0.022	0.023	0.026	0.026	0.026
	(1.372)	(1.347)	(1.422)	(1.509)	(1.516)	(1.530)
CapEx	0.060*	0.061*	0.059*	0.046	0.045	0.045
	(1.762)	(1.770)	(1.726)	(1.167)	(1.156)	(1.159)
Leverage	0.006	0.007	0.005	0.009	0.009	0.009
	(0.534)	(0.580)	(0.416)	(0.940)	(0.947)	(0.922)
ROA	0.002	0.002	0.002	0.004	0.004	0.005
	(0.424)	(0.453)	(0.316)	(0.876)	(0.878)	(0.884)
Obs.	13,892	13,892	13,892	11,958	11,958	11,958
R2 Adj.	0.518	0.518	0.517	0.532	0.532	0.532
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

***Table 5. Market-adjusted returns to natural disasters from 1996 to 2018 (Domestic Exposure)**. This table examines UK stock market reaction to natural disasters at the firm level. For this analysis, we retain only natural disasters that meet each of these criteria: (i) their duration is lower than 30 days; (ii) they caused at least £200 million in damage as reported by EM-DAT (in 2018 CPI-adjusted values); (iii) they are either a flood or a storm. We define a firm impacted if its headquarter is located in an affected area in a given date. In columns (1), (2) and (3), we define an area affected if a natural disaster happened in one of the first-level administrative divisions in the UK. In columns (3), (4) and (5), we define an area affected if a natural disaster happened in one of the second-level administrative divisions in the UK. In all columns, the dependent variable is the cumulative market-adjusted returns for treatment and control firms over the [-5,+5] period. All returns are adjusted using contemporaneous returns for the FTSE All Share Index. In column (2) and (5), $D_{i,t-1}^{High\ Exposure}$ takes the value of one if the physical climate risk ratio is greater than the yearly sample average the year before a natural disaster event. In columns (3) and (6), $D_{i,t-1}^{Proactive}$ takes the value of one if the year before a natural disaster a company had the climate proactive ratio (as defined in section 5) greater than zero and $D_{i,t-1}^{High\ Exposure}$ equals one. Continuous variables are winsorized at the 1% level. t-statistics are in parentheses and standard errors are double clustered at the firm-year level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.*

Dependent Variable: $CAR_{i,t}[-5,+5]$						
Hazard Granularity:		*ADL1*			*ADL2*	
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
$D_{i,t}^{Impacted}$	-0.000	-0.007	-0.004	-0.019***	-0.022***	-0.022***
	(-0.053)	(-0.331)	(-0.306)	(-4.705)	(-4.501)	(-4.493)
$D_{i,t-1}^{High\ Exposure}$		-0.008			0.003	
		(-0.702)			(0.640)	
$D_{i,t}^{Impacted} * D_{i,t-1}^{High\ Exposure}$		0.012			0.012**	
		(1.406)			(2.121)	
$D_{i,t-1}^{Not\ Proactive}$			-0.012			0.002
			(-0.854)			(0.453)
$D_{i,t-1}^{Proactive}$			0.002			0.005
			(0.167)			(0.841)
$D_{i,t}^{Impacted} * D_{i,t-1}^{Not\ Proactive}$			0.017			0.017***
			(1.329)			(4.084)
$D_{i,t}^{Impacted} * D_{i,t-1}^{Proactive}$			0.003			-0.002
			(0.410)			(-0.178)
Obs.	11,567	11,567	11,567	11,567	11,567	11,567
R2 Adj.	0.021	0.021	0.021	0.027	0.028	0.028
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

Table 6. Expected cash flows and volatility change analysis around natural disaster events in the UK. *This table examines UK stock market reaction to natural disasters happening in the UK at the second administrative level. In columns (1), (2) and (3), the dependent variable, $Downgrade_i$, equals one if the consensus in forecasted EPS for the fiscal-year end when a natural disaster happened decreases from 20 days before to 20 days after a natural disaster and 0 otherwise (as in Nagar & Schoenfeld (2022)). In columns (4), (5) and (6), the dependent variable is the change in daily stock return volatility from before to after a natural disaster event in percentage ($\Delta Vol_{i,t}$). 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-month period one year before the event. For this analysis, we retain only natural disasters that meet each of these criteria: (i) their duration is lower than 30 days; (ii) they caused at least £200 million in damage as reported by EM-DAT (in 2018 CPI-adjusted values); (iii) they are either a flood or a storm. In all columns, we define a firm impacted if its headquarters is located in an affected UK county in a given date. In column (2) and (5), $D_{i,t-1}^{High\ Exposure}$ takes the value of one if the physical climate risk ratio is greater than the yearly sample average the year before a natural disaster event. In columns (3), and (6), $D_{i,t-1}^{Proactive}$ takes the value of one if the year before a natural disaster a company had the climate proactive ratio (as defined in section 5) greater than zero and $D_{i,t-1}^{High\ Exposure}$ equals one. Continuous variables are winsorized at the 1% level. t-statistics are in parentheses and standard errors are double clustered at the firm-year level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.*

	$Downgrade_i$			ΔVol_i		
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
$D_{i,t}^{Impacted}$	0.003	0.005	0.005	0.016	0.029	0.019
	(0.235)	(0.338)	(0.339)	(0.285)	(0.321)	(0.168)
$D_{i,t-1}^{High\ Exposure}$		-0.031			-0.189**	
		(-0.824)			(-1.993)	
$D_{i,t}^{Impacted} * D_{i,t-1}^{High\ Exposure}$		-0.008			-0.046	
		(-0.155)			(-0.615)	
$D_{i,t-1}^{Not\ Proactive}$			-0.030			-0.045
			(-0.844)			(-0.902)
$D_{i,t-1}^{Proactive}$			-0.033			-0.091*
			(-0.642)			(-1.875)
$D_{i,t}^{Impacted} * D_{i,t-1}^{Not\ Proactive}$			-0.008			0.026
			(-0.104)			(0.353)
$D_{i,t}^{Impacted} * D_{i,t-1}^{Proactive}$			-0.008			0.026
			(-0.177)			(0.260)
Obs.	8,450	8,450	8,450	11,519	11,519	11,519
R2 Adj.	0.140	0.140	0.140	0.212	0.212	0.212
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

***Table 7. Regression results of closing spread and trading volume changes around natural disaster events in the UK**. This table examines UK stock market reaction to natural disasters happening in the UK at the second (i.e., county) administrative level. In columns (1), (2) and (3), 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 (4), (5) and (6), the dependent variable is the change in British-pound trading volume from before to after a natural disaster event in 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-month period one year before the event. For this analysis, we retain only natural disasters that meet each of these criteria: (i) their duration is lower than 30 days; (ii) they caused at least £200 million in damage as reported by EM-DAT (in 2018 CPI-adjusted values); (iii) they are either a flood or a storm. In all columns, we define a firm impacted if its headquarters is located in an affected UK county in a given date. In column (2) and (5), $D_{i,t-1}^{High\ Exposure}$ takes the value of one if the physical climate risk ratio is greater than the yearly sample average the year before a natural disaster event. In columns (3), and (6), $D_{i,t-1}^{Proactive}$ takes the value of one if the year before a natural disaster a company had the climate proactive ratio (as defined in section 5) greater than zero and $D_{i,t-1}^{High\ Exposure}$ equals one. Continuous variables are winsorized at the 1% level. t-statistics are in parentheses and standard errors are double clustered at the firm-year level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.*

	$\Delta Closing\ Spread_i$			$\Delta Trading\ Volume_i$		
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
$D_{i,t}^{Impacted}$	0.164**	0.189**	0.189**	-1.178***	-2.362***	-2.362***
	(2.227)	(2.477)	(2.463)	(-2.689)	(-3.347)	(-3.055)
$D_{i,t-1}^{High\ Exposure}$		-0.006			-0.505	
		(-0.115)			(-1.187)	
$D_{i,t}^{Impacted} * D_{i,t-1}^{High\ Exposure}$		-0.084**			1.148***	
		(-2.571)			(2.931)	
$D_{i,t-1}^{Not\ Proactive}$			-0.005			-1.159
			(-0.072)			(-1.171)
$D_{i,t-1}^{Proactive}$			-0.005			-0.851
			(-0.197)			(-1.047)
$D_{i,t}^{Impacted} * D_{i,t-1}^{Not\ Proactive}$			-0.123***			1.298***
			(-3.001)			(3.161)
$D_{i,t}^{Impacted} * D_{i,t-1}^{Proactive}$			-0.041			1.119
			(-1.102)			(1.150)
Obs.	11,483	11,483	11,483	10,456	10,456	10,456
R2 Adj.	0.225	0.225	0.225	0.218	0.218	0.218
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

Table 8. Firm Proactiveness to Physical climate Risks and Firm Compliance. *This table examines whether firms incurring in enforcement actions brought by government regulators in the UK are more likely to be proactive in managing their physical climate risk exposure. In all columns, the dependent variable,* $D_{i,t+1}^{Proactive}$*, is equal one if, in year t+1, the proactive ratio for a generic firm is greater than the median of the distribution of positive physical climate risk ratios. In all columns, we estimate a PROBIT model. In columns (1), (3) and (5),* $D_{i,t}^{Violation}$ *is a dummy variable taking the value of one if a firm committed at least one violation in year t. In columns (2), (4) and (6) "Log violation (£)" represents the log of the total amount (in £) of sanctions incurred by a firm in year t. In columns (1) and (2) we consider all types of violations provided in the Violation Tracker UK database. In columns (3) and (4), we retain only safety and environmental-related violations. In columns (5) and (6), we retain only environmental-related violations. All continuous variables are winsorized at the 1% level. t-statistics are in parentheses and standard errors are double clustered at the firm and year level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.*

Dependent Variable: $D_{i,t+1}^{Proactive}$	Any Violation		Environmental and Safety Violations		Environmental Violations only	
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{D_{i,t}^{Violation}}$	**0.030**		**0.103**		**-0.254**	
	(0.278)		**(0.993)**		**(-1.265)**	
Log violation (£)		**-0.003**		**0.002**		**-0.019**
		(-0.348)		**(0.157)**		**(-0.710)**
Log(TA)	0.102***	0.104***	0.102***	0.103***	0.104***	0.104***
	(6.590)	(6.930)	(6.508)	(6.721)	(6.782)	(6.698)
PPE	-0.164	-0.163	-0.164	-0.164	-0.155	-0.157
	(-1.531)	(-1.517)	(-1.533)	(-1.536)	(-1.449)	(-1.474)
B/M	-0.060*	-0.061*	-0.060*	-0.060*	-0.061*	-0.061*
	(-1.662)	(-1.693)	(-1.645)	(-1.680)	(-1.705)	(-1.703)
CapEx	0.957***	0.948***	0.968***	0.954***	0.925***	0.933***
	(2.803)	(2.799)	(2.846)	(2.823)	(2.734)	(2.791)
ROA	0.074	0.071	0.074	0.073	0.071	0.073
	(0.835)	(0.815)	(0.838)	(0.826)	(0.811)	(0.821)
Leverage	0.119	0.118	0.120	0.119	0.123	0.123
	(1.287)	(1.276)	(1.293)	(1.287)	(1.328)	(1.335)
$TM_{i,t}^{High\ Exp.}$	0.866***	0.870***	0.857***	0.866***	0.886***	0.880***
	(3.842)	(3.872)	(3.763)	(3.839)	(3.870)	(3.825)
Obs.	7,921	7,921	7,921	7,921	7,921	7,921
Pseudo R2	0.270	0.269	0.271	0.268	0.270	0.270
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Appendix

Table A1. Variable Definitions. *This table describes each variable used in our analyses and its relative source. Data Source are TRE = Thomson Reuters Eikon; CH = Companies House; W = Worldscope; F = FAME; CG = Compustat Global; G = GDIS; IBES = IBES; D = Thomson Reuters Datastream; V = Violation Tracker Database UK.*

Variable	Definition	Source
$TM_{i,t}^{High\ Exposure}$	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.	TRE, CH
Proactive Ratio	The frequency of unigrams or bigrams related to our physical climate risk dictionary in a generic annual report in the proximity of proactive verbs, divided by $TM_{i,t}^{High\ Exposure}$.	
$D_{i,t}^{Proactive\ (I)}$	A dummy taking the value of one if the climate proactive ratio is greater than zero.	TRE, CH
$D_{i,t}^{Proactive\ (II)}$	A dummy taking the value of one if the climate proactive ratio is greater than 50%.	TRE, CH
$D_{i,t}^{Proactive\ (III)}$	A dummy taking the value of one if the climate proactive ratio is greater than the median of the distribution of positive physical climate risk ratios in a certain year.	TRE, CH
$D_{i,t}^{Proactive\ (IV)}$	A dummy taking the value of one if the climate proactive ratio is greater than the median of the distribution of positive climate proactive ratios in a certain year.	TRE, CH
Log(TA)	Natural logarithm of firm's total assets.	W, F, CG
PPE	Property, Plant and Equipment, divided by total assets of the same year.	W, F, CG
B/M	Book value of shareholder equity, divided by the market capitalisation at the end of the fiscal year.	W, F, CG
ROA	Net income, divided by total assets of the same year.	W, F, CG
CapEx	Capital Expenditures, divided by total assets of the same year.	W, F, CG
Leverage	Total debt (= short-term debt + long-term debt), divided by the total assets.	W, F, CG
$D_{i,t}^{Impacted\ (World,\ ADL1)}$	A dummy taking the value of one if either the firm headquarter or one of its subsidiaries is located in an affected area at the first administrative level worldwide in a given year.	F,G
$D_{i,t}^{Impacted\ (World,\ ADL2)}$	A dummy taking the value of one if either the firm headquarter or one of its subsidiaries is located in an affected area at the second administrative level worldwide in a given year.	F,G
$D_{i,t}^{Impacted\ (UK,\ ADL1)}$	A dummy taking the value of one if either the firm headquarter or one of its subsidiaries is located in an affected area at the second administrative level in the UK in a given year.	F,G
$D_{i,t}^{Impacted\ (UK,\ ADL2)}$	A dummy taking the value of one if either the firm headquarter or one of its subsidiaries is located in an affected area at the second administrative level in the UK in a given year.	F,G

Table A2. Market-adjusted returns to natural disasters from 1996 to 2018 (Worldwide Exposure). *This table examines UK stock market reaction to natural disasters at the firm level. For this analysis, we retain only natural disasters that meet each of these criteria: (i) their duration is lower than 30 days; (ii) they caused at least £200 million in damage as reported by EM-DAT (in 2018 CPI-adjusted values); (iii) they are either a flood or a storm. We define a firm impacted if either its headquarter or one of its subsidiaries is located in an affected area in a given date. In columns (1), (2) and (3), we define an area affected if a natural disaster happened in one of the first-level administrative division worldwide. In columns (3), (4) and (5), we define an area affected if a natural disaster happened in one of the second-level administrative division worldwide. In all columns, the dependent variable is the cumulative market-adjusted returns for treatment and control firms over the [-5,+5] period. All returns are adjusted using contemporaneous returns for the FTSE All Share Index. In column (2) and (5), $D_{i,t-1}^{High\ Exposure}$ takes the value of one if the physical climate risk ratio is greater than the yearly sample average the year before a natural disaster event. In columns (3), and (6), $D_{i,t-1}^{Proactive}$ takes the value of one if the year before a natural disaster a company had the climate proactive ratio (as defined in section 5) greater than zero and $D_{i,t-1}^{High\ Exposure}$ equals one. Continuous variables are winsorized at the 1% level. t-statistics are in parentheses and standard errors are double clustered at the firm-year level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.*

Dependent Variable: $CAR_{i,t}[-5,+5]$						
Hazard Granularity:		*ADL1*			*ADL2*	
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
$D_{i,t}^{Impacted}$	0.003	0.003	0.003	0.000	-0.001	-0.002
	(1.056)	(0.910)	(0.770)	(0.008)	(-0.254)	(-0.268)
$D_{i,t-1}^{High\ Exposure}$		0.001			0.001	
		(0.875)			(0.659)	
$D_{i,t}^{Impacted} * D_{i,t-1}^{High\ Exposure}$		-0.000			0.004	
		(-0.100)			(0.896)	
$D_{i,t-1}^{Not\ Proactive}$			-0.001			0.002
			(1.091)			(0.792)
$D_{i,t-1}^{Proactive}$			0.000			0.001
			(0.557)			(0.267)
$D_{i,t}^{Impacted} * D_{i,t-1}^{Not\ Proactive}$			-0.001			0.006
			(-0.539)			(1.356)
$D_{i,t}^{Impacted} * D_{i,t-1}^{Proactive}$			0.003			0.008
			(0.423)			(1.523)
Obs.	382,810	382,810	382,810	107,551	107,551	107,551
R2 Adj.	0.017	0.017	0.017	0.022	0.022	0.022
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

Table A3. Market-adjusted returns to natural disasters from 1996 to 2018 (Worldwide Exposure – Different proxies of physical climate risk). *This table examines UK stock market reaction to natural disasters at the firm level. For this analysis, we retain only natural disasters that meet each of these criteria: (i) their duration is lower than 30 days; (ii) they caused at least £200 million in damage as reported by EM-DAT (in 2018 CPI-adjusted values); (iii) they are either a flood or a storm. We define a firm impacted if either its headquarter or one of its subsidiaries is located in an affected area in a given date. In columns (1), (2) and (3), we define an area affected if a natural disaster happened in one of the first-level administrative division worldwide. In columns (3), (4) and (5), we define an area affected if a natural disaster happened in one of the second-level administrative division worldwide. In all columns, the dependent variable is the cumulative market-adjusted returns for treatment and control firms over the [-5,+5] period. All returns are adjusted using contemporaneous returns for the FTSE All Share Index. In columns (1) and (4),* $Log(Damage1)_{i,t}$ *is measured as the natural logarithm of one plus Damage1, where Damage1 is calculated as the weighted average of disaster damages in areas where a firm location is located, using the fractions of exposed locations total assets as weights. In columns (2) and (5),* $Log(Damage2)_{i,t}$ *is measured as the natural logarithm of one plus Damage2, where Damage2 is calculated as the weighted average of disaster damages in areas where a firm location is located, using the fractions of exposed locations sales as weight. In columns (3) and (6),* $Log(Damage3)_{i,t}$ *is measured as the natural logarithm of one plus Damage3, where Damage3 is calculated as the weighted average of disaster damages in areas where a firm location is located, using the fractions of exposed employees as weight. Continuous variables are winsorized at the 1% level. t-statistics are in parentheses and standard errors are clustered at the firm-year level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.*

Dependent Variable: $CAR_{i,t}[-5,+5]$						
Hazard Granularity:		*ADL1*			*ADL2*	
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
$Ln(Damage1)_{i,t}$	0.000			-0.000		
	(1.151)			(-0.221)		
$Ln(Damage2)_{i,t}$		0.000			-0.000	
		(1.135)			(-0.314)	
$Ln(Damage3)_{i,t}$			0.000			-0.000
			(1.141)			(-0.302)
Obs.	382,810	382,810	382,810	107,551	107,551	107,551
R2 Adj.	0.017	0.017	0.017	0.022	0.022	0.022
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

Table A4. Market-adjusted returns to natural disasters from 1996 to 2018 (Domestic Exposure – Different Climate Adaptation Proxies). *This table examines stock market reaction to natural disasters happened at the second-level administrative division in the UK using different methodologies to construct the climate adaptation variables. The details of the event study are described in Table 5. In all columns, the dependent variable is the cumulative market-adjusted returns for treatment and control firms over the [-5,+5] period. In columns (1) and (5), we use the first definition of climate adaptation variable to construct $D_{i,t-1}^{Proactive}$. In columns (2) and (6), we use the second definition of climate adaptation variable to construct $D_{i,t-1}^{Proactive}$. In columns (3) and (7), we use the third definition of climate adaptation variable to construct $D_{i,t-1}^{Proactive}$. In columns (4) and (8), we use the fourth definition of climate adaptation variable to construct $D_{i,t-1}^{Proactive}$. All variables' definitions are provided in Appendix A.1. In columns (1), (2), (3) and (4), we construct the $D_{i,t-1}^{High\ Exposure}$ variable using the yearly sample mean of climate text measures. In columns (5), (6), (7) and (8), we construct the $D_{i,t-1}^{High\ Exposure}$ variable using the yearly sample median of climate text measures. Continuous variables are winsorized at the 1% level. t-statistics are in parentheses and standard errors are clustered at the firm-year level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.*

Dependent Variable: $CAR_{i,t}[-5,+5]$								
Hazard Granularity:	*ADL2*							
Sample Average Construction:	*Our methodology*				*Nagar and Schoenfeld (2022) methodology*			
Specification:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$D_{i,t}^{Impacted}$	-0.022***	-0.022***	-0.022***	-0.022***	-0.024***	-0.024***	-0.024***	-0.024***
	(-4.493)	(-4.499)	(-4.495)	(-4.501)	(-4.785)	(-4.792)	(-4.781)	(-4.799)
$D_{i,t-1}^{Not\ Proactive}$	0.002	0.003	0.002	0.003	0.001	0.002	0.002	0.002
	(0.453)	(0.742)	(0.525)	(0.597)	(0.284)	(0.480)	(0.380)	(0.418)
$D_{i,t-1}^{Proactive}$	0.005	-0.006	0.003	0.005	0.002	-0.010*	0.000	-0.002
	(0.841)	(-0.515)	(0.570)	(0.693)	(0.375)	(-1.752)	(0.015)	(-0.306)
$D_{i,t}^{Impacted} * D_{i,t-1}^{Not\ Proactive}$	0.017***	0.012**	0.017***	0.014**	0.013***	0.010**	0.012***	0.011**
	(4.084)	(2.445)	(3.892)	(2.576)	(2.906)	(2.419)	(3.000)	(2.550)
$D_{i,t}^{Impacted} * D_{i,t-1}^{Proactive}$	-0.002	-0.012	0.006	-0.004	0.000	0.004	0.006	-0.001
	(-0.178)	(-0.915)	(0.612)	(-0.356)	(0.023)	(0.401)	(0.666)	(-0.126)
Obs.	11,567	11,567	11,567	11,567	11,567	11,567	11,567	11,567
R2 Adj.	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.028
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES

Table A5. Placebo Tests. *This table examines UK stock market reaction to natural disasters at the firm level. The details of the event study are described in Table 5. In columns (1), (2) and (3), we assign to each natural disaster a false date that is 30 calendar days before its true date. In columns (4), (5) and (6), we assign to each natural disaster a false date that is 30 calendar days after its true date. Continuous variables are winsorized at the 1% level. t-statistics are in parentheses and standard errors are clustered at the firm-year level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.*

Dependent Variable: $CAR_{i,t}[-5,+5]$						
Hazard Granularity:	*ADL2*					
Placebo Dates:	*30 Days Before the event*			*30 Days After the event*		
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
$D_{i,t}^{Impacted}$	0.001	0.002	0.002	-0.001	-0.002	-0.002
	(-0.670)	(-0.946)	(-0.960)	(-0.705)	(-0.815)	(-4.662)
$D_{i,t-1}^{High\ Exposure}$		-0.004			0.001	
		(-0.53)			(0.021)	
$D_{i,t}^{Impacted} * D_{i,t-1}^{High\ Exposure}$		0.002			0.006	
		(1.132)			(0.014)	
$D_{i,t-1}^{Not\ Proactive}$			0.005			0.004
			(0.091)			(1.047)
$D_{i,t-1}^{Proactive}$			0.004			0.002
			(0.557)			(1.103)
$D_{i,t}^{Impacted} * D_{i,t-1}^{Not\ Proactive}$			-0.001			0.005
			(-0.167)			(0.159)
$D_{i,t}^{Impacted} * D_{i,t-1}^{Proactive}$			0.001			0.007
			(0.423)			(0.918)
Obs.	11,567	11,567	11,567	11,567	11,567	11,567
R2 Adj.	0.021	0.021	0.021	0.021	0.021	0.021
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

Table A6. Sensitivity analysis of market adjusted returns with different proactive dummies specifications. *This table shows the percentages of significant coefficients of the two main regressors in eq. (3) across 1,000 combinations, which is defined as follow:*

$$CAR_{i,t}[-5,+5] = \alpha_i + \beta_1 D_{i,t}^{Impacted} + \beta_2 D_{i,t-1}^{Not\ Proactive} + \beta_3 D_{i,t-1}^{Proactive} + \beta_4 D_{i,t-1}^{Not\ Proactive} * D_{i,t}^{Impacted} + \beta_5 D_{i,t-1}^{Proactive} * D_{i,t}^{Impacted} + \beta_6 \boldsymbol{X_{i,t}} + \theta_i + e_{t,i.}$$

The first row shows the results for β_4 in eq. (3), while the second row shows the results β_5 in eq. (3). Each column corresponds to a specific $D_{i,t}^{Proactive}$ measure (defined in Section 5). Specifically, $D_{i,t}^{Proactive}$ can take the value of one if, in a certain year, the proactive ratio for a generic firm is: i) greater than zero (first column); ii) greater than 0.5 (second column); iii) greater than the median of the distribution of positive physical climate risk ratios (third column); iv) greater than the median of the distribution of positive proactive ratios (fourth column). In each row, we consider a general beta as "significant" if it is at least significant at the 5% level.

Coefficient	(1)	(2)	(3)	(4)
β_4	99%	91.45%	83.05%	78.05%
β_5	*3.15%*	*14.95%*	*16.8%*	*21.65%*

Table A7. Correlation Matrix for text mining dummies in Eq. (3). *This table shows the Pearson correlation coefficients for the main variables in eq. (3), which is defined as follow:*

$$CAR_{i,t}[-5,+5] = \alpha_i + \beta_1 D_{i,t}^{Impacted} + \beta_2 D_{i,t-1}^{Not\ Proactive} + \beta_3 D_{i,t-1}^{Proactive} + \beta_4 D_{i,t-1}^{Not\ Proactive} * D_{i,t}^{Impacted} + \beta_5 D_{i,t-1}^{Proactive} * D_{i,t}^{Impacted} + \beta_6 \boldsymbol{X_{i,t}} + \theta_i + e_{t,i.}$$

	$\boldsymbol{D_{i,t}^{Impacted}}$	$\boldsymbol{D_{i,t-1}^{Not\ Proactive}}$	$\boldsymbol{D_{i,t-1}^{Proactive}}$	$\boldsymbol{D_{i,t-1}^{Not\ Proactive} D_{i,t}^{Impacted}}$	$\boldsymbol{D_{i,t-1}^{Proactive} D_{i,t}^{Impacted}}$
$\boldsymbol{D_{i,t}^{Impacted}}$	1				
$\boldsymbol{D_{i,t-1}^{Not\ Proactive}}$	0.006	1			
$\boldsymbol{D_{i,t-1}^{Proactive}}$	0.009	-0.114	1		
$\boldsymbol{D_{i,t-1}^{Not\ Proactive} D_{i,t}^{Impacted}}$	0.300	0.334	-0.038	1	
$\boldsymbol{D_{i,t-1}^{Proactive} D_{i,t}^{Impacted}}$	0.338	-0.038	0.332	-0.013	1