Disaster Management

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Abstract

Climate change is making natural disasters more frequent and severe, yet little is known about the capacity of firms to withstand such disasters and adapt to them. We examine these issues using the World Management Survey (WMS), which includes new questions on firms' climate change perceptions and climate adaptation behavior as well as management practices. Combining WMS with geocoded data on natural disasters, we create a panel spanning 8,000 firms across 33 countries over three decades. We show that exposure to disasters hurts firm survival and subsequent growth. Firms with structured management practices are more resilient, suffering much smaller drops in jobs growth and lower exit risk. Exploring mechanisms, we show that firms with more structured management practices have more accurate perceptions of climate-related risks to their businesses and are also more likely to have implemented measures to adapt to climate change. Our results suggest that structured management practices shape firms' resilience to climate shocks, highlighting management as a policy-relevant margin for mitigating the harmful consequences of climate change.

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1 Introduction

Climate change has made natural disasters more frequent and this trend is likely to continue over the coming decades (IPCC 2023). The impact of natural disasters on firm performance is therefore a growing economic and political concern. While a considerable body of research has documented that natural disasters tend to have negative economic impacts, little is known about how firm capabilities can ameliorate this negative effect. There is also a paucity of evidence on the extent to which firms are perceiving and adapting to the increased frequency of natural disasters and other risks induced by climate change.

In this paper we address both of these evidence gaps by examining the relationship between natural disasters, management practices and firm outcomes. We combine surveys on management practices (including a new wave of the World Management Survey, WMS), with performance data from digitized company accounts (BVD Historical Orbis) and natural disaster data from the Geocoded Disasters Dataset (E. L. Rosvold and Halvard Buhaug 2021). This novel data combination spans 33 countries over 30 years from 1984 to 2018. Using this data, we show that being exposed to natural disasters increases the probability of exit and decreases subsequent growth. We find that structured management practices protect firms from some of these negative impacts as better-managed firms experience significantly smaller reductions in jobs growth and lower exit risk immediately following a disaster. Looking over longer horizons, we find the negative effects of disasters and the offsetting effect of management generally attenuate over time, consistent with management primarily reducing short-run disruption rather than generating persistent post-disaster divergence.

Exploiting novel questions in the latest WMS wave, we distinguish between two channels through which management practices may shape firms' resilience to climate-related risks. First, we examine *perception*-driven mechanisms and show that firms with more structured management are more likely to perceive climate change as a risk, especially when they are located in areas that have recently experienced natural disasters. Second, we study firms' *adaptive* responses and find that firms with more structured management are also more likely to implement measures to reduce climate-related risks, both overall and conditional on a given level of perceived risk. Together, these results suggest that management practices enhance resilience both by improving firms' ability to interpret climate-related signals and by strengthening their capacity to act on those signals.

The paper is structured as follows. We discuss the related literature in the rest of the introduction before describing the data we use to measure firm management practices, outcomes and their exposure to natural disasters in Section 2. Section 3 presents results on the impacts of natural disasters on firm outcomes and how management mediates these impacts. Section 4 provides evidence of two channels whereby management can reduce the negative impact of disasters by examining associations between management, climate change risk perceptions and adaptation to such risks. Section 5 concludes. Online Appendices give more details on the data (Appendix A) and results (Appendix B).

We contribute to at least three literatures. First, we relate to work examining the importance of management practices for economic performance. A large body of recent work has documented how management practices appear to be an important driver of firm-level and

macro-level productivity.[1] However, relatively little is known about *why* management matters so much. One under-explored mechanism is that structured management practices enable firms to be more resilient to negative shocks. An exception is Lamorgese et al. (2024) and Li et al. (2023) who find that firms with high quality management were more resilient during the COVID-19 pandemic. The pandemic was a rarer event than theincreasingly prevalent natural disasters that are our focus.[2]

Another reason for the positive association between structured management practices and economic outcomes is that firms with such practices are more able to process and respond to relevant information. Supporting this hypothesis, we find firms with structured management have more accurate perceptions of climate-related risk and adopt measures to reduce their exposure to these risks. This is consistent with Bloom et al. (2026), who find a positive association between management practices and the accuracy of firms' forecasts both of their own future performance and that of the economy as a whole. It also provides empirical evidence that structured management practices can contribute to firms' 'dynamic capabilities' (Teece 2007), via an improved awareness of environmental risks. Some papers emphasise that managerial dynamism can improve business performance through greater appreciation of economic factors such as market trends (Augier and Teece 2009), we find this also applies to awareness of factors in the natural (rather than business) world, which can threaten firms' operations.

Some existing papers examine links between management and climate change mainly focusing on climate change mitigation (i.e., actions to reduce their emissions). An early example finding a positive association between climate mitigation and management practices was Bloom et al. (2010), who study of over 300 UK manufacturing firms documenting that those with more structured management were not only more productive but also less energy and carbon intensive. Martin et al. (2012) find similar patterns using a measure of specifically green (rather than general) management practices, whereas Capelle et al. (2024) provide evidence from a global sample of publicly listed firms that 'laggards' with high energy intensity relative to others in their industry and country exhibit relatively poor management practices. An interpretation of these correlations is that managers may be better informed about the costs and benefits of energy efficiency improvements and suffer less from present-bias (Allcott et al. 2014). Haas et al. (2022) provide direct evidence of this channel by drawing on World Bank surveys in emerging economies to show firms with better green management practices invest more in green technologies. Shin (2023) provides evidence of another mechanism between management practices and energy use, showing that firms with structured management practices are more responsive to increases in fuel prices.

Far fewer authors have examined links between management and climate change adaptation (i.e. actions taken by firms to reduce the impact of negative environmental shocks on their performance), which is the focus of this paper. Indeed, the only work on this subject that we are aware of is Adhvaryu et al. (2022), which shows how management can reduce the negative impact

1. See Scur et al. (2021) for a recent survey using the WMS. Other examples are provided by Bandiera et al. (2020), Bianchi and Giorcelli (2022), Bloom and Van Reenen (2007), Bloom et al. (2019), Bloom et al. (2020), Bruhn et al. (2018), Giorcelli (2019), Huber et al. (2021), Iacovone et al. (2022), and Lazear et al. (2015).

2. Aghion et al. (2021), find that more decentralised firms performed better throughout the negative shocks of the financial crisis. We show that decentralization and other potential correlates of management do not drive our results.

of pollution shocks on productivity. Using detailed data on productivity, task assignments, and managerial characteristics within a large Indian garment firm, they find that air pollution shocks negatively impact worker-task productivity but that managers are able to mitigate the impact of such shocks by reallocating negatively-affected workers to less pollution-sensitive tasks. Importantly, they document significant heterogeneity in the efficacy of such mitigation according to manager attentiveness: a one standard-deviation increase in manager attentiveness almost entirely offsets the negative productivity impact of pollution experienced by the average manager. Despite the specificity of Adhvaryu et al's setting and their focus on productivity at the granular worker-task level, their findings are consistent with our own to the extent that manager attentiveness can be interpreted as an example of better management practices. We view our more general study as a complement to their work: we provide evidence from multiple countries that good management practices mitigate the negative impacts of various environmental shocks, whereas Adhvaryu et al. show the channels by which management practices influence mitigation in a particular setting.

A second substantial body of related work examines the economic impacts of extreme weather and natural disasters, spanning analyses at the country level (Dell et al. 2012; Acevedo et al. 2020), the local level (Kocornik-Mina et al. 2020; Elliott et al. 2015), and the firm level. Within this last strand, a growing literature documents significant productivity losses from climatic shocks. Zhang et al. (2018) use detailed production data on Chinese manufacturing firms to establish an inverted-U relationship between temperature and productivity, with high temperatures generating particularly large negative effects. Somanathan et al. (2021) similarly find that a one-degree Celsius temperature rise reduces annual output among Indian manufacturing plants by approximately 2%, driven primarily by the effect of heat on labour productivity. Extending the focus beyond temperature, Clò et al. (2024) show that exposure to floods and landslides increases firm exit and reduces sales and employment among Italian firms, with effects concentrated among small and low-tech establishments. Our paper contributes to this literature by showing that structured management practices are an important dimension of *heterogeneity* of natural disaster impacts across firms.

Several papers extend the analysis of firm-level disaster impacts beyond direct effects, considering how inter-firm networks cause shocks to propagate. Barrot and Sauvagnat (2016) find that natural disasters in the US that affect supplier firms in production networks also cause losses in output and market value among downstream consumer firms. The impacts they find are particularly pronounced if the impacted supplier produces relatively specific inputs making it difficult for downstream consumers to substitute to other, non-affected firms. Tanaka (2015) and Carvalho et al. (2021) both examine how the impact of the 2011 Great East Japan Earthquake and subsequent tsunami was amplified via firm networks. Carvalho et al. (2021) focus on domestic firm networks and document transmission of negative disaster impacts both up and down supply chains while Tanaka (2015) shows the impact of the event extended beyond Japan itself with negative impacts on the output of US branches of Japanese multinationals in proportion with the reliance of the US firms on inputs from Japan. In contrast to these papers, we focus on the impacts that extreme environmental events have on firms that are themselves exposed to

such disasters.[3] Given the consistent evidence of indirect impacts provided by these papers, our omission of such propagation effects means our findings should not be interpreted as estimates of the comprehensive economic impact of disasters. Rather, our focus is on documenting whether heterogeneity in the effects of disaster exposure can be attributed to differences in management practices, which we indeed find to be a mediator of direct negative firm-level impacts.

Third, we contribute to an expanding and politically-salient literature related to climate change adaptation. A large proportion of work in this area focuses on agricultural adaptation, highlighting the capacity for insurance and novel technologies to reduce the negative effects of environmental shocks (for example see Dar et al. (2013), Auffhammer and Carleton (2018), Michler et al. (2019) and Hultgren et al. (2022)). Empirical studies of adaptation among non-agricultural firms are less numerous but have documented several changes in firm practices that can mitigate the adverse effect of climate shocks such as the adoption of LED lights (Adhvaryu et al. 2020), worker responses such as timing of breaks (Masuda et al. 2021), and changes in supplier networks (Balboni et al. 2023). In relation to this literature, our results suggest management practices constrain firms' ability to implement such adaptive changes and document an 'adaptation gap' between well- and poorly-managed firms.

2 Data

Our aim is to examine the relationship between firm performance, management practices and natural disasters. In this section we describe the data we use to measure each of these factors and document the characteristics of our analysis sample. More details are in A.

2.1 Firm Outcomes and Management Practices

Given our focus on the relationship between firms' management practices and the impacts of natural disasters, we take data on firms from the latest version of the World Management Survey (WMS). The WMS is an interview-based survey conducted by trained analysts who engage middle managers in semi-structured conversations aboutdaily practices within their respective establishments, as outlined by Bloom and Van Reenen (2007). The interview format is designed to prevent interviewees from providing responses they believe the interviewer wants to hear and covers a range of practices related to operations, monitoring, target setting, and people management systems. Within each of these areas, there are 18 topics, with each topic assessed on a scale from 1 (indicating little to no structure or weak practices) to 5 (indicating well-structured or best practices). Pooling across all WMS survey waves results in a dataset of 17,783 observations of 13,721 firms.

We construct indices of management from the individual WMS scores by z-scoring each question, averaging across all management questions within a firm and then z-scoring again the resulting measure to obtain an overall management score with mean zero and standard deviation 1. Similar management indices constructed from the WMS data have been shown to

3. As explained in section 2, our measure of 'exposure' is defined as being located within a 40km radius of a disaster's centre. Therefore, while we do not explicitly aim to measure indirect impacts of disasters that arise through supply network linkages, the effects we estimate may implicitly capture localised indirect impacts due to suppliers that are located close to the firm.

have significant predictive power of a range of dimensions of performance, with more structured firms having higher productivity, profitability and growth rates (Scur et al. 2021).

In the second part of our empirical analysis we examine two possible channels through which management may mediate the impact of natural disasters on firms: awareness of climate-related risks and adoption of measures to mitigate such risks. To explore these issues, we leverage the following questions in the 2022 wave of the WMS

1. *Climate Risk Perception* "Would you say things like rising temperatures, natural disasters, and changing seasonal weather patterns can put the operation of your manufacturing site at risk?"

2. *Climate Adaptation* "Do you have any measures in place that are responses to the potential effects of climate change? Can you tell me about some of these measures?"

As with the management scores these are on a 1 to 5 scale, which we standardise.[4]

Two issues arise over the climate-related questions. First, the wording of the climate risk perception question means a firm could answer 'no' if they did not regard climate change as a material threat to their operations or if they did regard climate change as a risk but believed the actions they had taken were sufficient to protect their manufacturing site. However, the discursive nature of the WMS survey process means that the initial response is followed by subsequent 'why' questions. The eventual score against this question is given based on an assessment of the initial and follow-up answers and will therefore reflect any evidence that firms' have considered temperature, disaster or weather-related risks as factors that could compromise their operation. Second, the wording of the perception question is relatively suggestive compared to the management practice questions in the WMS, in that it explicitly highlights a number of distinct examples of climate-related risk. While this may push respondents toward a 'yes' answer to some extent, in practice around a third of companies are scored 1-2 against this question, indicating little awareness whereas only 16% are given a score of 5, indicating thorough and considered awareness.

To measure firms' financial outcomes we combine the WMS with Historical Orbis (HO), a database of essentially all the registered firms in the countries in our data. HO has digitised versions of their company accounts enabling the construction of a panel dataset containing employment, capital (fixed assets), value added and survival. Changes in company identifiers mean we are unable to match all WMS firms with an HO record. Furthermore, since accounting standards differ over what information must be disclosed between countries, firm size classes and time periods, not all WMS firms have full information on inputs and outputs.[5] We are able to obtain some financial information for 11,629 of the 13,721 WMS firms resulting in a panel of 175,525 firm-year observations. To include as much of this panel as possible in the empirical analysis, we linearly interpolate continuous firm-level information collected in the WMS between

4. Examples of actions firms report under the climate adaptation question are provided in Figure B4 and Table B20 in Appendix B.

5. Firm information recorded in HO is sometimes at a higher level than in the WMS, for example if the entity surveyed in WMS is a plant of a larger company. The HO database also frequently contains multiple records for a given company-year observation if, for example, companies publish financial reports in both annual reports and local registry filings. We proceed by taking mean financial variables within an HO firm-year combination and combining with the WMS data at the lowest level possible.

waves for firms observed multiple times in the WMS. For firms that are observed only once in the WMS, we backfill their WMS-recorded characteristics for up to five years prior to their survey date.[6]

2.2 Natural Disasters and Disaster Exposure

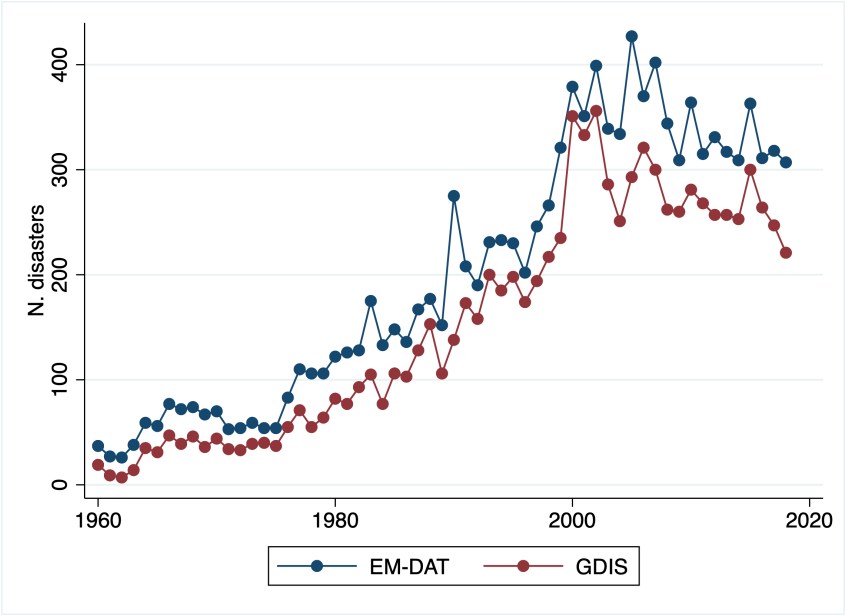
Data on natural disasters are taken from the Geocoded Disasters Dataset (GDIS) (E. L. Rosvold and Halvard Buhaug 2021). GDIS contains geocoded information on natural disasters recorded in the Centre for Research on the Epidemiology of Disasters' Emergency Events Database (EM-DAT), between 1960 and 2018. The EM-DAT database is a worldwide record of complex emergencies with natural disaster information covering floods, storms, earthquakes, volcanic activity, extreme temperatures, landslides, droughts, and (dry) mass movements. An event must meet specific criteria related to its impact to be included in the EM-DAT database. Generally, an event is considered for inclusion if it results in ten or more deaths, 100 or more people affected, a declaration of a state of emergency, or a call for international assistance. Combining information from various sources, including government reports, international organisations and news agencies, the database is regarded as a relatively comprehensive record of natural disasters and has been used in several previous studies of their effects including Kahn (2005), Besley and Persson (2009) and Cavallo et al. (2013).

EM-DAT provides standardised information on events' date, type, impact, and the number of casualties, but lacks standardised measures of disaster location. Locations are recorded as the names of affected places with no standardised unit and sometimes are recorded as geographical features, such as a mountain range, rather than a particular settlement. GDIS adresses this by matching the location names in EM-DAT to standardised units taken from the Global Administrative Areas database (GADM 2018) and obtains latitude and longitude coordinates of the unit centroids. GDIS only includes disasters located with what the data creators deemed to be an adequate degree of accuracy. In practice, 85% disaster-locations in EM-DAT were successfully geocoded with floods and earthquakes achieving nearly-100% and droughts the lowest coverage at 64%. Since the majority of disasters in EM-DAT are floods and storms, the two datasets track each other closely (see Figure 1).[7]

6. In practice, this only influences our measure of employee skill composition when analysing the impact of disasters on firm performance. We show in Appendix Table B18 that our main results are quantitatively similar if we do not use the interpolated or backfilled data.

7. Appendix Figures A1 and A2 show the number of disasters by type and country respectively. Further details on the algorithm used by the creators of GDIS to obtain disaster locations is provided in (E. Rosvold and H. Buhaug 2021). In 2014 EM-DAT enhanced its location data by geocoding natural disaster records, with the exception of biological disasters, starting from the year 2000 onwards. Geocoding was conducted by matching textual information on the affected area to Global Administrative Unit Layers (FAO) area codes. GDIS geocoded EM-DAT disasters using similar approach but starts in 1960 rather than 2000 and, in some cases, contains geographic data at a finer spatial resolution than the geocoded EM-DAT. We use GDIS rather than the geocoded version of EM-DAT for these reasons.

Figure 1: Natural Disasters Recorded in EM-DAT and GDIS



To measure firms' exposure to natural disasters, we first geolocate firms in the WMS by searching Google Maps for their name, country and, if present, city and zipcode using the Google Maps Geocoding API. The API call returns the coordinates of the location that best matches the input string, although fails if no match or only an imprecise match is found. Of 13,721 WMS firms we are able to accurately geolocate 10,154.[8] We then calculate the linear distance between firms' precise location and the location centroid for every natural disaster recorded in GDIS and classify firms as exposed to any particular event if this linear distance is less than or equal to a threshold distance.

Several considerations influence the choice of the threshold distance used to define disaster exposure. While a narrow threshold confines the disaster exposure definition to firms that are proximate to, and thus likely more affected by, disasters, it also reduces the number of 'disaster exposed' observations. Narrow thresholds may also miss spillover effects to firms located in areas surrounding those affected by a disaster, such as changes in local demand and labour markets. Absent any 'correct' way to balance these considerations, we estimate our main results using various disaster exposure thresholds ranging from 20km to 70km. Results presented in the main body of this paper are based on classifying a firm as exposed to a particular event using a 40km threshold, since results obtained using this definition are representative (in terms of sign and significance) of those obtained using both narrower and wider thresholds. We present additional estimates of our main specifications using the full range of thresholds in Appendix Figure B3. Using the 40km-based definition of disaster exposure, we take the count of disasters a firm is exposed to in a given year and construct a binary measure of disaster exposure if this sum is greater than 0.

While the location information provided in GDIS is a considerable improvement on that available in EM-DAT, there are two significant reasons why it remains an imprecise record of

8. To improve accuracy, we disregard geocode results that pertain to the centroid of an administrative area e.g. a state/country.

natural disaster locations. First, the algorithm used to geolocate EM-DAT disasters failed in some instances where the EM-DAT location was either very general, such as a river running through large parts of a country, or non-unique within a country. Second, the specific latitudes and longitudes assigned to a disaster pertain to the centroids of the affected administrative units rather than boundaries that demarcate the extent of the disaster and are therefore approximations of the true boundaries of affected areas. Since a single disaster can be associated with multiple administrative units, the precision of this approximation is inversely related to the granularity of the administrative units: for example, it is safer to assume the entirety of a unit was flooded by an event ascribed to the centre of the unit when the unit is a village rather than a state. Although the highest spatial resolution in GDIS corresponds to administrative level 3 (usually district), the vast majority of the locations are administrative level 1 (typically state/province). Such imprecision of GDIS event locations therefore introduces a degree of measurement error into our measures of firms' exposure to disasters: our measure will omit disasters that GDIS failed to geocode and may incorrectly classify a firm as exposed if the area truly impacted by the disaster is further away than that implied by a GDIS centroid.

Appendix B.1 formally examines the implications of disaster exposure misclassification for our analysis. If misclassification is not systematically related to management, measurement error attenuates estimates of the impact of disasters on firms and the extent to which these impacts are mitigated by management practices. More generally, if misclassification varies systematically with management, estimated coefficients may in principle be biased in either direction. To assess whether differential misclassification is a concern in our setting, we compare floods and storms recorded in GDIS to a distinct flood dataset, which relies more heavily on satellite-derived measures of inundation. While alignment between the two sources is not perfect, the results reported in Appendix B.1 provide no evidence that misclassification is systematically related to management practices. This suggests that any misclassification of disaster exposure in our data is more likely to attenuate estimated effects than to generate misleading results. The fact that we observe significant impacts of disasters on firms despite such attenuation bias reassures us that our measure of disaster exposure, while inevitably imperfect, retains adequate signal to provide insight.

2.3 Sample Characteristics

Table A2 has sample means for some key variables. Our analysis sample is restricted to firms in the WMS that were successfully geolocated and matched to accounting data. The WMS has a sampling frame of manufacturing firms with between 50 to 5,000 employees, so results may not be generalisable to very small firms (where there may be less need for formal structured management practices) and mega-firms.[9] Previous work shows that compared to this frame of medium sized manufacturing firms, WMS respondents are broadly balanced on observable characteristics such as size, productivity and industry.[10] Table A2 shows that relative to the full WMS sample, our firms are more European predominantly due to higher coverage in the HO data. They have very slightly higher levels of management practices (0.01 of a standard

9. Table A1 in Appendix A shows the country composition of our analysis sample.
10. For example, see Bloom and Van Reenen (2007), Bloom et al. (2014) and Bloom et al. (2024).

deviation) and are about 6% larger, but are otherwise statistically similar.

3 The Impact of Natural Disasters on Firm Performance

3.1 Econometric Strategy

In this section we examine the impact of natural disasters on firm performance and whether such impacts are offset by better management practices. First, we focus on the impact of natural disasters ignoring any heterogeneity in their effects. Our empirical strategy exploits variation in the timing of natural disasters. As emphasized by Borusyak and Hull (2023), research designs that rely on plausibly exogenous shocks can be biased when units exhibit predictable variation in their exposure to those shocks.[11] In our setting, predictable exposure arises if certain types of firms disproportionately locate in areas with persistently high disaster risk, for example due to historical specialization or offsetting locational advantages such as market access. Moreover, because disaster incidence is serially correlated, firms observed in high-risk areas may differ systematically from other firms as a result of past disaster exposure, potentially inducing correlation between disaster exposure and firm performance.

To address these concerns, we follow the recommendation of Borusyak and Hull (2023) to model and control for expected shock exposure. Specifically, we estimate expected disaster occurrence, $\mathbb{E}[D]_{it}$, as the fitted value from a regression of the form:

$$D_{it} = \kappa_c D_{iPRE10} + \phi_t + e_{it}, \tag{1}$$

where D_{it} is the disaster exposure of firm i in time t as discussed in Section 2, D_{iPRE10} is a set of dummies for the number of disasters within 40km of firm i in the 10 years prior to the first time we observe the firm, ϕ_t are year dummies and e_{it} is the error term. The κ_c allow the impact of D_{iPRE10} to be specific to country c. This specification captures persistent, location-specific disaster exposure, which we then control for in regressions that relate disaster occurrence to firm performance.

By conditioning on expected disaster exposure, identification of disaster effects is therefore based on residual variation in disaster timing conditional on underlying risk. Under the assumption that such residual variation is orthogonal to firms' performance trajectories, the causal effect of disaster exposure can be estimated using:

$$\Delta y_{ijct+1} = \beta_0 D_{it} + \beta_1 M_i + \beta_2 X_{it} + \beta_3 \mathbb{E}[D]_{it} + \tau_t + \iota_j + \kappa_c + \epsilon_{it}. \tag{2}$$

Δy_{ijt+1} is the growth (between $t+1$ and t) of a particular outcome such as inputs, outputs or is a dummy for survival. M_i is our WMS measure of structured management practices, X is a vector of firm characteristics including firm age, the share of employees with a degree and firm size. To avoid any mechanical correlation, firm size is measured as log fixed assets when the outcome variable is employment growth and as log employment otherwise.[12] τ, ι and κ are

11. We thank an anonymous referee for drawing our attention to this result and its relevance for our analysis.

12. To increase sample size, we include observations missing components of X_{it} by setting the missing characteristic to zero and including a dummy variable that identifies the observations.

vectors of time, 2-digit industry j and country of location dummies respectively and ϵ the error term (we cluster standard errors by firm to allow within-firm correlation).

We examine whether management practices affect the impact of natural disasters using generalisations of equation (2) of the following form:

$$\Delta y_{ijct+1} = \beta_0 D_{it} + \beta_1 M_i + \beta_2 X_{it} + \beta_3 \mathbb{E}[D]_{it} + \beta_4 (D_{it} * M_i) + \beta_5 (D_{it} * X_{it}) + \tau_t + \iota_j + \kappa_c + \epsilon_{it}. \quad (3)$$

This specification allows the effect of disaster exposure to vary with firm characteristics. The coefficient of primary interest is β_4, which captures whether the impact of natural disasters differs systematically with structured management practices. We also include interactions between disasters and other firm attributes, X_{it}, to accommodate heterogeneity in disaster impacts along other observable dimensions, and de-mean any variable interacted with the disaster indicator so that the β_0 coefficient can be interpreted as the impact of disaster on a firm with average characteristics. In addition, we consider a more parsimonious variant of equation (3) that excludes the $(D_{it} * X_{it})$ terms. Comparing estimates of β_4 across these specifications sheds light on whether heterogeneity in disaster impacts associated with management operates directly, or indirectly through firm characteristics correlated with management.

The Δy_{ijct+1} we consider include survival, a dummy that equals one if the firm exits between t and $t+1$ (or longer windows in some specifications) and zero otherwise. Aside from survival, all outcomes we consider are *changes* in firm-level metrics such as capital, employment and value added. Specifically,

$$\Delta y_{ijct+s} = \frac{\ln(y_{it+s}) - \ln(y_{it})}{s}, \quad (4)$$

where x is capital, employment, value added. Our baseline is the one period growth rate, $s = 1$, but we also consider higher values of s to examine whether impacts are short-lived or persist over several years and normalise by the lag considered s, to make growth rates annualised and so comparable across time horizons. By focusing on growth rates, any constant differences across firms in the levels of outcomes are differenced out. We trim growth rates at the top and bottom 2% level to reduce the impact of outliers.

Several points regarding equation (2) warrant further discussion. First, while the specification echoes those of conventional event-studies, it includes a single disaster indicator rather than pre- and post-event dummies or distributed leads and lags. We adopt this approach because defining clean dynamic profiles is complicated when firms experience multiple disasters within short time windows, which - although uncommon - does occur in our data. Appendix B presents complementary evidence from distributed-lag models following Dell et al. (2012). These results are consistent with the dynamic patterns obtained from equation (3) and are discussed further alongside our main results.

A second issue concerns whether the coefficients on D and its interactions can be interpreted as capturing the causal impact of disasters on firm performance. As discussed above, our principal identification assumption is that the timing of disasters is exogenous to firm performance conditional on controls. Beyond the concern that disaster exposure is predictable addressed above, a distinct concern is reverse causality. Disaster exposure could itself affect management practices, in which case the interaction term $(D_{it} * M_i)$ might reflect endogenous changes in

management rather than heterogeneity in disaster impacts. This would be especially problematic for our empirical approach if the firms that change their management practices following disaster exposure were on different growth trajectories to firms that were exposed to disasters but did not change their management practices. In Appendix we use a subsample of firms that were surveyed at least twice by the WMS to directly test whether disaster exposure predicts changes in management practices and whether any affects differ according to firms' pre-disaster growth trajectory. Across specifications, we find management practices are highly persistent and that there is no systematic evidence of disaster exposure affecting changes in management practices. These results allay concerns of reverse causality and strengthen the interpretation of the interaction coefficients in equation (3) as capturing heterogeneity in the response of firm performance to disasters.

Finally, the strategic location of firms could, in principle, generate correlation between management practices and disaster exposure if better-managed firms systematically sort into locations with lower (or higher) disaster risk. Such sorting would bias the estimated disaster and disaster–management interaction effects by conflating the impact of disasters with pre-existing differences in firms' location choices and growth trajectories. However, Appendix Table A3 shows no significant association between management practices and disaster exposure once we condition on the firm characteristics included in our main specifications.

3.2 Main Results

Table 1 shows regression estimates where the dependent variable is capital growth in column (1), employment growth in column (2), value added growth in column (3) and survival in column (4).[13] Different panels are restricted and full versions of equation (3), with year and country fixed effects controlled for in all panels. Panel A starts with the management correlations and shows that firms with higher management scores have significantly faster growth in inputs (first two columns), output (third column) and survival (final column). Panel B has the same specification substituting disasters for management on the right hand side. This validates the disaster variable, showing that exposure to natural disasters reduces growth in firms' capital, employment and value added as well as reducing the probability of firms' survival. The estimates of these effects are economically important when compared to the mean value of the outcome variables: impacts on growth in capital, employment and value added growth amount to 17%, 52% and 27% reductions relative to the mean observed growth rates, while the impact on firm survival corresponds to roughly a 23% increase in the firm exit rate.[14] Panel C has management and disaster in the same regressions and includes additional linear controls, showing the coefficients on disaster remain essentially unchanged.

13. Table B6 in Appendix B.3 shows estimates where the dependent variable is growth in profits and in total factor productivity. There is some evidence that disasters have a negative effect on these outcomes, although significance is generally lower. While coefficients on the management-disaster interaction are positive, they are insignificant. We therefore focus our analysis on the inputs, output and survival measure shown in Table 1.

14. Recall that our firms are in the manufacturing sector, where growth is relatively slow.

Table 1: Impact of disaster exposure and management on one year ahead firm performance

	(1)	(2)	(3)	(4)
	Log differences $(t, t+1)$			
	Capital	Emp.	VA	Survival
Panel A: Linear Management				
Management	0.0024**	0.0018**	0.0041***	0.0181***
	(0.0011)	(0.0008)	(0.0013)	(0.0047)
Panel B: Linear Disaster Exposure				
Disaster in year	-0.0046**	-0.0032**	-0.0088***	-0.0406***
	(0.0023)	(0.0014)	(0.0030)	(0.0112)
Panel C: Linear Firm Characteristics				
Disaster in year	-0.0041*	-0.0026*	-0.0084***	-0.0450***
	(0.0023)	(0.0014)	(0.0030)	(0.0112)
Management	0.0016	0.0017**	0.0064***	0.0090*
	(0.0011)	(0.0008)	(0.0014)	(0.0050)
Panel D: Linear Firm Characteristics and Management-Disaster interaction				
Disaster in year	-0.0040*	-0.0025*	-0.0084***	-0.0447***
	(0.0023)	(0.0014)	(0.0030)	(0.0112)
Management	0.0014	0.0010	0.0056***	0.0038
	(0.0012)	(0.0009)	(0.0015)	(0.0054)
(Management)* (Disaster)	0.0011	0.0039***	0.0043	0.0287**
	(0.0023)	(0.0014)	(0.0031)	(0.0120)
Panel E: Linear Firm Characteristics and Full Disaster interactions				
Disaster in year	-0.0040*	-0.0023*	-0.0083***	-0.0457***
	(0.0023)	(0.0014)	(0.0030)	(0.0112)
Management	0.0015	0.0012	0.0055***	0.0038
	(0.0012)	(0.0009)	(0.0015)	(0.0054)
(Management)* (Disaster)	0.0007	0.0027*	0.0044	0.0292**
	(0.0024)	(0.0015)	(0.0033)	(0.0125)
Dep. var. mean	0.026	0.006	0.033	0.982
N obs.	73869	59487	33700	112783
N firms	5288	4706	2580	7899

Note: standard errors in parentheses clustered at the firm level. Differences in sample size across columns are due to missing values in the HO financial data. Dependent variable in columns (1)-(3) are one-year differences in the log of the outcome denoted in the column title defined according to equation (1). Dependent variable in column (4) is a dummy equal to 1 if the firm survived to year $t+1$ and zero if it exited. Coefficients and standard errors in column (4) are multiplied by 10. */**/*** denote significance at the 10/5/1 percent level respectively.

Panel D of Table 1 is a key result, which includes the interaction between disasters and management from equation (3). Panel E additionally includes interactions between other firm characteristics and disaster exposure. In both panels, firms with higher management scores have a significantly higher survival probability following disaster exposure than those with lower scores. Having a one standard deviation higher management score offsets about 60% of the impact of disaster exposure (in Panel D, $0.0287/0.0447 = 0.64$). Even conditional on survival, jobs growth is significantly worse in disaster areas for firms with less structured management practices. The magnitude of the interaction coefficient is roughly equal to the linear disaster

effect indicating that firms with one standard-deviation higher management scores experience essentially no negative impacts of disaster exposure on growth. While the point estimated effects on survival are quantitatively similar in Panel E, the introduction of other disaster interactions causes the point estimate of the management-disaster interaction on employment growth to fall indicating that some of the mediating effect of management is due to differences in other firm characteristics. The interactions of management and disasters is also positive for capital growth and value added growth, although these are not significant at conventional levels.

[ANK 2026/03/08: I understand why you've added the following section, but I'm a bit wary about the 'intensive' v 'extensive' margin exposition. The way it's currently written reads as if the outcome variable is in levels instead of growth rates. We also have the issue that the sample size changes across specifications. The robustness check in Table B9 that drops exiting firms and shows the coefficients are stable is a more direct way of addressing R1's selection concern. The decomposition exercise, by contrast, doesn't actually address the selection problem (it treats the employment growth coefficient as a clean intensive margin effect, which is precisely what R1 questions in their discussion of selection), and the cumulation over a decade contradicts our own dynamic results showing attenuation at longer horizons. The referees have not asked for this, so perhaps it's best to omit?] In order to give a rough idea of the relative magnitude of the survival vs. growth effects, consider two industries that are identical in all respects except the "high management industry" has management scores one standard deviation larger than the "low management industry". Assume that both industries are simultaneously hit by a disaster and responses are given by the coefficients in Panel E of Table 1. The initial relative impact on jobs in the high management vs. low management industry due to the survival effect is $\beta_4^S = 0.0029$, the coefficient on the management interaction in the survival regression. In addition to this extensive margin effect on jobs, there is an intensive margin effect which is $\beta_0^L = 0.0027$ the coefficient on the management interaction in the employment growth regression. This gives an overall effect of $\beta_4^S + \beta_0^L = 0.0056$. In other words, a disaster causes jobs to initially fall 0.5% faster in the low management industry. This is about half due to the intensive margin and half the extensive margin.

Note however that the intensive margin effect will cumulate over time. For example, after a decade, the intensive margin effect is an order of magnitude larger to the survival effect. Taken literally, this means that employment will be over 3% lower in the low vs. high management industry following the disaster shock, with 90% of this due to the intensive margin.

These are, of course, very much back of the envelope estimates as we have not fully specified an equilibrium model where there are many other potential responses (such as on entry), so do not want to over-claim. Nonetheless, these suggest the magnitudes in Table 1 are substantial and driven by extensive and intensive margins.

3.3 Dynamic Effects

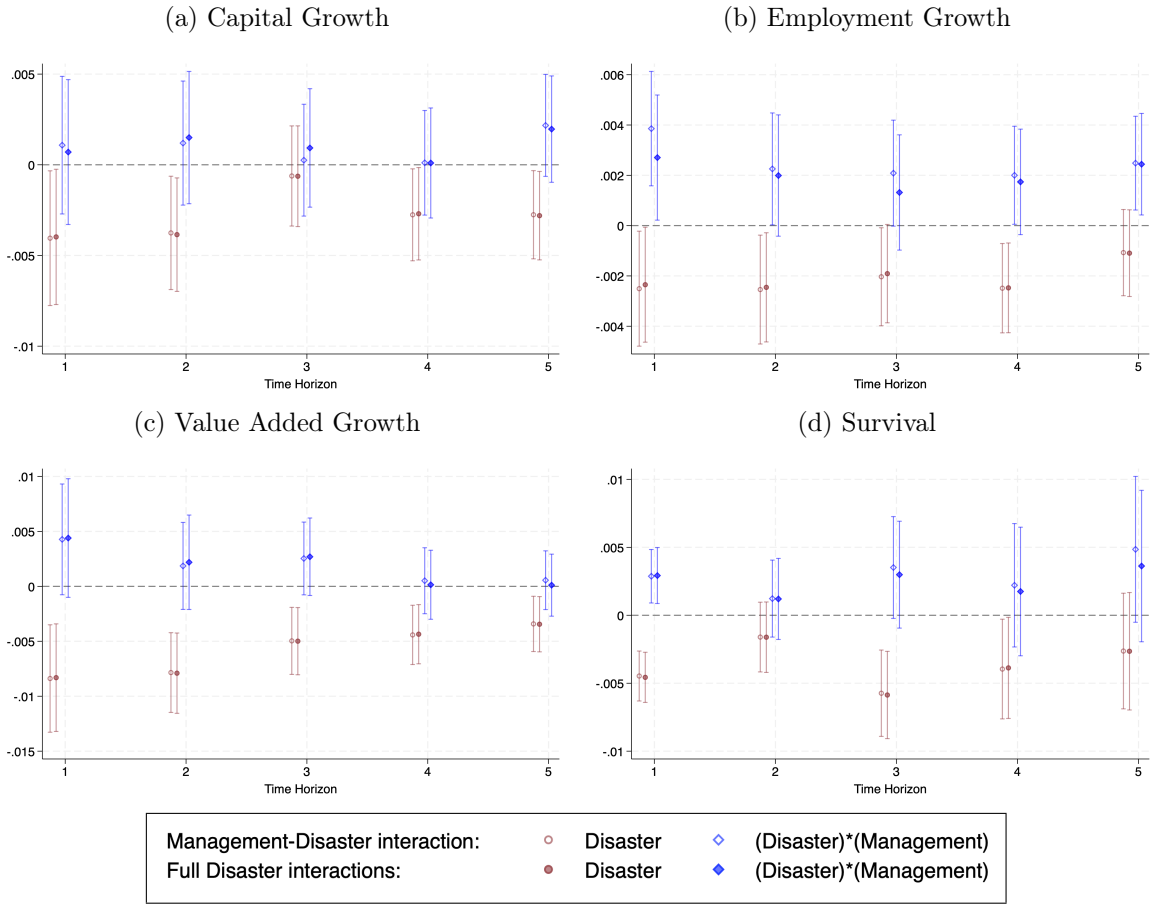
The analysis so far focuses on one-year ahead impacts. To examine the dynamic effects of disaster exposure, and the extent to which they depend on management practices, we re-estimate equation (3) examining outcomes 2, 3, 4 and 5 years after a disaster occurs. This approach is

analogous to the local projections method of Jordá (2005), which has become a standard tool for estimating impulse responses in panel settings. Each panel of Figure 2 displays the estimates and 90% confidence intervals of equation (3), reflecting the linear impact of disasters (β_0) and the extent to which this is mediated by structured management practices (β_4). The x-axis is the time horizon where "1" replicates Panels D (unshaded) and E (shaded) of Table 1.

Several patterns emerge from Figure 2. First, looking at the direct negative effects in red in the lower part of each panel (β_0), we see that the negative impacts on inputs and output growth tend to dissipate over time, especially for value added. The pattern for survival is noisier, with standard errors becoming wider at longer horizons.

Second, turning to the offsetting effect of management, we see that the disaster–management interactions in blue (β_4) are strong in initial year or two for growth in employment and in value added. For value added, the offsetting resilience of management fades out over the longer term, whereas for employment it persists. For capital growth, the effects are qualitatively similar across time horizons but quite imprecise. For survival, the management effect persists but, similarly to the direct disaster effect, becomes considerably less precise at longer horizons.

Figure 2: Main Parameter Estimates Over Different Time Horizons



Note: figure shows estimates of the β_0 and β_4 parameters from equation (3) obtained when outcomes defined over various time horizons, indicated by the x-axis labels. Maroon circles represent the β_0 disaster effect, while blue diamonds represent the β_4 coefficient on the interaction of management practices with disaster exposure. The hollow markers that are slightly offset to the left show estimates from a specification where only management is interacted with disaster exposure (equivalent to Panel D of Table 1), while the solid markers slightly offset to the right show estimates from a specification where all firm characteristics are interacted with disaster exposure (equivalent to Panel E of Table 1). The dependent variable in Panels (a) to (c) is the x-year annualised growth rate of the variable in the subfigure title, where x is the number of years between t and $t + x$. In Panel (d) the outcome is a binary indicator for survival by at least year $t + x$. Bars indicate 90% confidence intervals.

Appendix Tables B7 to B10 examine dynamic impacts using distributed-lag models similar to those used by Dell et al. (2012) to examine the impact of temperature shocks. In line with the results above, the negative impact of disasters are strongest in the year or two after impact. The offsetting effect of management for employment growth and survival is also strongest in the first year, with no significant evidence of an effect at longer lags. For capital growth, Table B7 shows little impact of the management interaction in the year of disaster exposure, but a strong positive and significant coefficient on the interaction with a one-year lag. This suggests that firms with more structured management suffer less pronounced slow downs in capital growth in the medium run following disaster exposure, but with a delayed effect. This is likely to be because of higher adjustment costs of capital investment.

Taken together, the dynamic results indicate that management practices play a meaningful role in cushioning the initial real effects of natural disasters on firms particularly in terms of employment and survival. The resilience effect appears stronger in the initial year of disaster

exposure than in subsequent years.

3.4 Heterogeneity and Robustness

In Appendix B.3, we conduct a battery of robustness checks of the results in Table 1 and analyse heterogeneity along several dimensions. We summarise some of these results here.

Considering first heterogeneity of the treatment effects, an important question is whether the protective effect of management varies with a country's level of development. We examine this by defining a high-income country indicator and interacting it with all regressors in specification (3), allowing disaster effects, management effects, and their interaction to differ across income groups.[15] Table B11 presents the results. In the survival regressions, the management–disaster interaction is large and significant for the low-income base group, but the triple interaction with high income is of similar magnitude and opposite sign, so that the total management–disaster effect for high-income countries is close to zero and statistically insignificant. This pattern is consistent with institutional substitution: in high-income countries, firms may have better access to insurance markets, disaster relief, and credit facilities that support survival regardless of internal management quality, whereas in low-income countries these external buffers are relatively absent and a firm's own organisational capacity becomes the critical margin determining whether it survives a disaster.

Second, we examine the degree of disaster severity, drawing on additional information recorded in EM-DAT regarding the number of recorded deaths and displaced population due to each disaster. We classify a disaster as "severe" using two criteria. First, a disaster is deemed severe if it is in the top 25% of all disasters in terms of either deaths or number of displaced people (these thresholds correspond to 44 deaths and approximately 21,300 people displaced). Second, in addition to these aggregate thresholds, disasters in a particular country are categorized as severe if they are in the top 5% of disasters according to country-specific deaths or number of displaced people. Table B12 contains the results from including a severe disaster indicator alongside our baseline disaster measure. We find that severe disasters drive the management results, with the management-disaster interactions in the survival and employment growth regressions only significant for the severe disaster indicator.

Third, we disaggregate the overall management score which is an average across 18 dimensions. We group these dimensions into four categories of operations, monitoring, targets and people (HR practices). Table B13 summarises the results. The results lose precision slightly as using a smaller number of practices to construct the separate indices adds noise to the management variables (which are strongly correlated with each other). Nonetheless, the "Targets" dimension of management appears to have the strongest positive interaction. This captures the extent to which firms set ambitious (yet achievable) targets and regularly evaluate performance against them.

Next we consider robustness. First, as described in Section 2, our measure of disaster exposure is based on whether a firm is located within 40 km of a disaster recorded in GDIS.

15. We classify countries as high income according to their World Bank income level classification in 2018, which is the last year of our sample in this analysis (World Bank 2023). Countries' income category is given in Table A1.

Figure B3 in Appendix B.3 shows that the estimated disaster–management interaction effects are broadly robust to alternative definitions of exposure using distance thresholds between 20 and 70 km. The interaction estimates are similar in magnitude, or larger, when using thresholds below 40 km, but attenuate as the distance threshold increases.

Second, as noted in the literature review, some papers have found that decentralized firms are more resilient to negative shocks (e.g., Aghion et al. (2021)). The WMS survey also includes several questions on the degree of decentralization within a firm, reflecting the degree to which a plant manager has autonomy from the central headquarters. Since the structured management score is positively correlated with this measure, one may be concerned that our results are driven by decentralisation rather than by management *per se*. Table B14 presents the results of panels D and E of Table 1 additionally controlling for decentralisation and its interaction with disasters. Decentralised firms do have significantly higher employment growth and are more likely to survive. But, in contrast with management, none of the interactions between decentralisation and disaster exposure are significant, whereas the coefficients on the disaster-management interactions in the employment growth and survival equations remain positive and significant

Third, while our baseline specification includes country, year and two-digit industry fixed effects, Table B15 additionally includes year dummies interacted with one-digit industry and year-by-region fixed effects. The estimates of the disaster-management interaction term on employment growth and on survival are similar to those presented in Table 1. Moreover, Table B16 shows that our results are robust to additionally including linear time trends that differ by two-digit industry and by country.

Finally, columns (1)-(4) of Table 1 relate to firm performance conditional on survival. To examine whether selection among surviving firms is materially driving these estimates, Table B17 contains results from the same specifications as Table 1 estimated on a "survivor" subsample, where we drop any firm that is observed as exiting our data within one year of disaster exposure. Restricting the analysis to surviving firms and those that never experience a disaster leads to no discernible change on the disaster–management interaction for employment growth, suggesting that selective exit is not a primary driver of our baseline results.

Overall, our results on the resilience effects of management for survival and job growth appear robust. In terms of heterogeneity, the greater resilience of firms with structured management practices seems particularly strong in developing countries, for the most severe disasters and for the targets element of management.

4 Management Practices, Climate Risk Perceptions and Climate Change Adaption

The results of the previous section suggest structured management practices protect firms from some of the negative impacts of natural disasters. There are numerous mechanisms through which this could arise. To structure our discussion of these mechanisms, it is useful to distinguish between pathways that operate via of firms' perceptions of disaster risk and pathways that operate independently from such perceptions.

Perception-driven mechanisms operate through firms' awareness of climate-related risks. Within this class of mechanisms, we further distinguish between two distinct channels. The first, which we term "perception-contingent adaptation", arises if management practices lead to more accurate perceptions of disaster risks in disaster-exposed locations, which in turn drive adaptive actions. This channel operates through the causal chain whereby management enhances risk awareness, which then motivates adaptation. The second perception-driven channel, which we term "enhanced perception-responsiveness", operates differently. Even conditional on any given level of perceived risk, well-managed firms may be more effective at translating their risk perceptions into concrete adaptive actions. This reflects superior organisational capacity to act on perceived threats, independent of whether management also improves the accuracy of those perceptions. The distinction between these two perception-driven mechanisms is important because they have different policy implications, which we discuss below.

Non-perception mechanisms, by contrast, can arise if well-managed firms exhibit greater organisational resilience through capabilities that are in place independent of firms' perceptions of disaster risk. Features such as internal reallocation capacity, supply-chain robustness, and access to financial liquidity can help mitigate the impact of a wide range of disruptions, including natural disasters. To the extent that these characteristics are more prevalent among firms with relatively structured management practices, they can insulate such firms from disaster impacts even if natural disasters are not regarded as a salient threat to their operations.

Beyond an analytic device, this three-way distinction is meaningful as the different mechanisms have different policy implications. If perception-contingent adaptation were the main reason firms with more structured management are resilient to disasters, then improving risk awareness in less structured firms may be sufficient to enhance their disaster resilience. Informational and educational campaigns on disasters are potential instruments. If enhanced perception-responsiveness were more important, then interventions would need to focus not just on risk awareness but also on organisational capabilities to translate awareness into action. If, by contrast, non-perception mechanisms were the dominant factor, then policy interventions targeting disaster risk awareness would be less effective than interventions that aimed to improve firms' general management structures.

In this section, we provide evidence relevant to these mechanisms by exploiting questions in the latest wave of the WMS that asked firms about their perception of risks related to climate change and whether they have taken any actions to reduce these risk (i.e. whether they have engaged in climate change adaptation).[16] Evidence consistent with perception-driven adaptation would arise if structured management practices are positively associated with perceived climate risk or if the relationship between perceived risk and adaptation is stronger among better-managed firms. A positive association between management and reported adaptation conditional on perceived disaster risk, meanwhile, would suggest that generic organisational resilience is an important mechanism.

We first examine evidence relevant to perception-driven mechanisms by analysing the association between management practices and perception of climate risks. Since we can only conduct this analysis on the most recent WMS wave, we consider different natural disaster exposure

16. The specific wording of these questions is provided in section 2.

measures to those in the previous section. Rather than identify firms that have been exposed to a natural disaster in a particular year, we instead aggregate natural disasters by decade and construct binary indicators that take the value of 1 if a firm's location is within 40km of at least one disaster in a particular decade and zero otherwise. These disaster exposure indicators can therefore be considered backward-looking measures of the riskiness of firms' locations, in contrast to the measures in the previous section that captured whether a firm had itself been exposed to a disaster. As well as examining the association between the climate scores and disasters in the most recent decade of the GDIS data (the period spanning 2010-2018), we also control for exposure to disasters in the 1970s. This is because the wording of the climate risk perception and adaptation questions explicitly refers to *changes* in climate patterns, suggesting any association between recent natural disaster exposure and the scores on these questions may be stronger among firms in areas that had not been hit by natural disasters in the past.

To be precise, we examine the impact of management practices on disaster perception using variants on the following specification:

$$\begin{aligned} P_i = &\gamma_0 D_{i,2010s} + \gamma_1 M_i + \gamma_2 X_i + \gamma_3 (M_i * D_{i,2010s}) + \gamma_4 (X_i * D_{i,2010s}) + \\ &\gamma_5 D_{i,1970s} + \iota_j + \kappa_c + \epsilon_i, \end{aligned} \tag{5}$$

where P is a firms' standardised risk perception score and D_{i2010s} denotes a dummy for being located in disaster-exposed area in the 2010s (and equivalently for the 1970s). We are specifically interested in the parameters γ_1 and γ_3.

Table 2 examines how firms' perceptions of climate change risk vary with recent disaster exposure and management practices. Column (1) shows that disasters are positively, but insignificantly associated with risk perceptions. Column (2) shows that firms with more structured management practices are significantly more likely to perceive climate risks compared to other firms. A one standard deviation in the management score is associated with an increase of 0.1 of a standard deviation in the risk perceptions index. The final column shows that the management coefficient is driven by firms who have recently experienced a disaster.[17]

To assess whether these patterns merely reflect generic responses to adverse shocks, rather than responsiveness to events with a clear link to climate change, we examine heterogeneity by disaster type and replicate the analysis separately for floods and storms, which are plausibly affected by climate change, and earthquakes, which are not. These results are reported in Appendix Tables B21 and B22. For floods and storms, the estimated effects closely mirror those obtained using the aggregate disaster measure. In contrast, for earthquakes there is no evidence that risk perceptions respond to earthquake exposure either linearly or when interacted with management. The linear management coefficient remains positive and statistically significant in these specifications, indicating that better-managed firms are, on average, more likely to perceive climate change as a risk, but do not appear to condition these perceptions on exposure to non–climate-related shocks.

17. This pattern could be explained by at least two channels: firms with structured management practices may update their perceptions of climate risk to a greater extent following local disasters than other firms, or they may have strong general priors about the exposure of their local area to changing risk exposure. Since we only observe climate risk perceptions in the latest wave of the WMS, we are confined to cross-sectional analysis and therefore cannot distinguish between these alternative hypotheses.

Overall, Table 2 provides evidence that firms with more structured management processes are more likely to be aware of the risks posed by natural disasters than other firms (i.e., that they have more accurate disaster risk perceptions). This parallels the work of Bloom et al. (2026), who find a positive association between firms' management and the accuracy of their forecasts, both of their own year-ahead performance and that of the wider economy.[18]

Table 2: Perceptions of Climate Change Risk and Management

	(1)	(2)	(3)
Any Disaster 2010-2018	0.011	-0.002	-0.000
	(0.079)	(0.077)	(0.079)
Management		0.097***	0.005
		(0.035)	(0.055)
(Management) * (Disaster 2010-2018)			0.205***
			(0.073)
Any disaster 1970-1979	-0.170*	-0.208**	-0.223**
	(0.102)	(0.100)	(0.102)
(Management) * (Disaster 1970-1979)			-0.208**
			(0.087)
N obs.	1117	1117	1117
Industry Dummies	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes
Linear Firm Characteristics	No	Yes	Yes
Firm Char.-Disaster Interactions	No	No	Yes

Note: standard errors in parentheses clustered at the firm level. Dependent variable is firms' standardised climate risk perception score. Firm characteristics include log(employment), firm age and share of the workforce with a degree. */**/*** denote significance at the 10/5/1 percent level respectively.

While Table 2 provides suggestive evidence that perception-driven adaptation may be a mechanism behind the greater resilience of some firms to natural disasters, greater perceptions of disaster risk alone are unlikely to materially influence resilience unless they prompt specific actions by firms to ready themselves for the realisation of such risk. We therefore next examine climate adaptation directly by estimating variants of the following equation:

$$\begin{aligned} A_i = &\delta_0 D_{i2010s} + \delta_1 M_i + \delta_2 P_i + \delta_3 (M_i * P_i) + \delta_4 X_i + \delta_5 (M_i * D_{i2010s}) \\ &+ \delta_6 (X_i * D_{i2010s}) + \delta_7 D_{i1970s} \iota_j + \kappa_c + \epsilon_i, \end{aligned} \tag{6}$$

where A_i is a firm's standardised climate adaptation score and all other notation is as before. In addition to firm attributes M_i and X_i, in some specifications we also include firms' climate risk perception score P as an explanatory variable, since it is plausible that firms who perceive climate change to be a risk to their business are doing more to reduce such risks. We also allow

18. Table B23 in Appendix B repeats the most comprehensive specification in Table 2 for the separate components of management practices. This shows the interaction between management and disaster exposure is positive and significant across all dimensions of management, with the strongest effect on the targets management score.

the propensity of firms to act on their risk perceptions to differ according to their management practices by including the interaction term $M_i * P_i$.

Table 3 contains estimates of the main parameters of interest from equation (6). Column (1) shows that recent disaster exposure has a positive and significant association with climate risk adaptation. The management score has a large and strongly positive association with adaptation - a one standard deviation in the management score is associated with an increase of 0.31 of a standard deviation in the adaptation index. Column (2) includes the risk perception index which, as one might expect, enters with a positive and significant coefficient. The coefficient on management falls slightly, suggesting some of the adaptation-management relationship is through the fact that structured management aids greater risk perception as shown in Table 2. However, the fall of the coefficient on management is small, from 0.31 to 0.28. This implies that there are effects of management over and above any influence of perceptions. Column (3) includes an interaction between management and risk perception. The coefficient is large and significant, implying that firms with more structured management adapt more for a given level of risk perception. This is consistent with the enhanced perception-responsiveness hypothesis. Column (4) includes an interaction of recent disasters with management. Consistent with the previous table, the coefficient is positive but imprecisely estimated. The final column shows that the results are robust to a wider set of controls.[19]

19. Tables B24 and B25 in Appendix B repeat the analysis of Table 3 separately for floods/storms and earthquakes. Both these types of natural disaster yield results are similar to those of Table 3, although the linear effect of disaster exposure on adaptation is somewhat smaller for earthquakes than for floods/storms. Table B26 reports the most comprehensive specification in column (5) of Table 3 re-eastimated using the different components of management. The linear management effect is strongest for the targets component, whereas the interaction between management and climate risk perceptions is strongest for the operations component.

Table 3: Association Between Climate Change Adaptation, Management and Disaster Exposure

	(1)	(2)	(3)	(4)	(5)
Any Disaster 2010-2018	0.157**	0.146*	0.135*	0.137*	0.121
	(0.077)	(0.075)	(0.075)	(0.075)	(0.074)
Management	0.311***	0.275***	0.268***	0.218***	0.224***
	(0.033)	(0.032)	(0.032)	(0.053)	(0.053)
(Management) * (Disaster 2010-2018)				0.055	0.060
				(0.068)	(0.066)
Risk perception		0.215***	0.219***	0.219***	0.216***
		(0.030)	(0.030)	(0.031)	(0.031)
(Management) * (Risk perception)			0.090***	0.088***	0.087***
			(0.030)	(0.030)	(0.030)
N obs.	1117	1117	1117	1117	1117
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes	Yes
1970s Disasters	Yes	Yes	Yes	Yes	Yes
Linear Firm Characteristics	No	Yes	Yes	Yes	Yes
Firm Char.-Disaster Interactions	No	No	No	No	Yes

Note: standard errors in parentheses clustered at the firm level. Dependent variable is firms' standardised climate change adaptation score. Firm characteristics include log(employment), firm age and share of the workforce with a degree. */**/*** denote significance at the 10/5/1 percent level respectively.

An important caveat to these results is that we are looking at cross sectional correlations due to data constraints. Nonetheless, taken together, the results of this section provide some suggestive evidence that the greater disaster resilience of firms with more structured management, as documented in Section 3, operates through all three channels: perception-contingent adaptation (better risk awareness in relevant contexts leading to action), enhanced perception-responsiveness (superior ability to act on perceived risks) and non-perception mechanisms (generic organisational resilience). The direct effect of management on perception appears to be somewhat quantitatively weaker than the other two mechanisms however. The presence of all three mechanisms suggests that policies to improve disaster resilience among firms will need to address both risk awareness and organisational capabilities, rather than focusing on either dimension in isolation.

5 Conclusions

This paper shows that natural disasters have a range of negative impacts on firm performance. Analysing data from 33 countries spanning 35 years, we find exposure to a natural disaster increases firm exit and decreases growth in capital, employment and value added among surviving firms. We also find that structured management practices mitigate some of these negative effects, as firms with relatively strong management practices experience smaller reductions in employment growth and lower exit rates following natural disaster exposure. Such greater re-

silience of well-managed firms is primarily driven by differential performance following severe natural disasters and is strongest for firms' target setting practices. These results indicate that management practices play an important role in mitigating the near-term real effects of disasters.

Looking beyond the immediate aftermath, we find that the estimated interaction effects between management practices and disaster exposure remain generally positive at longer horizons, but become less precisely estimated. While these estimates are noisy, their pattern suggests attenuation rather than reversal: firms with weaker management practices tend to experience larger initial declines and subsequently recover, whereas better-managed firms exhibit greater stability in the face of shocks. Together, the dynamic evidence points to management practices reducing the immediate severity of disaster impacts rather than generating sharply divergent long-run growth paths.

To understand the mechanisms behind these patterns, we distinguish between three channels through which management practices may enhance disaster resilience. Perception-contingent adaptation occurs when management practices lead to more accurate risk perceptions in disaster-exposed locations which then motivate adaptive actions. Enhanced perception-responsiveness, by contrast, operates when well-managed firms are more effective at translating any given level of risk perception into concrete measures. In addition to these two perception-based mechanisms, non-perception mechanisms operate through generic organisational capabilities, such as internal reallocation capacity, supply-chain robustness, or access to liquidity, which are in place independent of firms' awareness of disaster risks.

Drawing on novel survey data on climate risk perceptions and adaptation, we provide evidence in support of all three channels. We find that management practices shape how firms process climate-relevant information: well-managed firms located in disaster-exposed areas exhibit elevated risk perceptions compared to both well-managed firms elsewhere and poorly-managed firms in exposed areas, and are more effective at translating perceived risks into adaptive actions conditional on the level of those perceptions. At the same time, well-managed firms report greater climate adaptation even conditional on their risk perceptions, suggesting that generic organisational capabilities play an important protective role.

These findings have important but nuanced implications for policy. The presence of all three mechanisms suggests that policies to improve disaster resilience among poorly-managed firms will need to address both risk awareness and organisational capabilities, rather than focusing on either dimension in isolation. Interventions aimed solely at increasing awareness of climate-related risks may increase firms' adoption of protective measures, but will have limited impact if organisational or financial constraints prevent firms from acting on heightened risk perceptions. Conversely, interventions designed to strengthen firms' organisational foundations — such as structured target-setting processes or practices that support supply chain flexibility — can enhance resilience without needing to influence firms' risk perceptions. The most effective policies are likely to combine elements that improve both risk awareness in relevant contexts and organisational capacity to act on that awareness.

At the same time, our findings also raise broader questions about the aggregate implications of firm-level resilience. While better management reduces short-run disruption and exit risk, disaster-induced exit of firms with weaker management may potentially facilitate reallocation

toward more efficiently managed firms. Whether policies should prioritize firm-level resilience or permit market-driven reallocation likely depends on the magnitude of adjustment costs and institutional context. In environments with high adjustment costs, such as rigid labor markets or limited access to finance for new entrants, policies that improve firms' management practices may avoid costly reallocation processes and preserve employment. In settings where reallocation is relatively frictionless, by contrast, selective exit following disasters may play a productive role in improving allocative efficiency. The appropriate policy response is therefore likely to be context-specific, depending on institutional features, the severity of transition costs, and social preferences regarding short-run stability versus long-run efficiency.

More generally, our analysis highlights the value of distinguishing between resilience driven by generic organisational capabilities and resilience that arises through more targeted adaptation. Understanding the relative importance of each of these mechanisms, how they interact with national institutions and market frictions, and how firm-level resilience shapes aggregate adjustment to climate change all represent important directions for future research. Integrating firm-level evidence on resilience with models of entry, exit, and reallocation would help clarify the aggregate consequences of climate-related shocks and the trade-offs implied by policies that target firm survival versus adjustment. Furthermore, examining how national institutions and policies such as labour market regulations or disaster relief programs shape the relationship between management practices and disaster responses would valuably inform the design of climate adaptation policy across different institutional contexts.

A large body of evidence shows that management practices are strongly associated with firm productivity and performance (Bloom et al. 2019). Our findings indicate that their relevance extends to firms' ability to cope with and adapt to natural disasters. As the economic consequences of climate change become more pronounced, understanding how managerial capabilities shape firms' resilience, learning, and adjustment will be central to both managerial decision-making and policy design.

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A Supplementary Data Information

World Management Survey

The WMS has been conducted in multiple waves between 2004 and 2022, covering 33 countries and composed of a repeated cross section and a panel. Details of the methodology are available at $https://worldmanagementsurvey.org/data/dwms-public-sector/wms-methodology/$. Management practices were scored following the methodology of Bloom and Van Reenen (2007). There are 18 question topics scored between 1 and 5 and we z-score each question to have mean zero and a standard deviation of one. Our baseline results are based on an aggregate management score constructed by taking the mean across all 18 topics and z-scores this to construct a basic index of structured management practices. Supplementary results consider four management sub-components: *operations* (three practices), *monitoring* (five practices), *targets* (five practices), and *incentives* (five practices). The shop-floor operations section focuses on the introduction of lean manufacturing techniques, the documentation of processes improvements, and the rationale behind introductions of improvements. The monitoring section focuses on the tracking of performance of individuals, reviewing performance, and consequence management. The targets section examines the type of targets, the realism of the targets, the transparency of targets, and the range and interconnection of targets. Finally, the incentives/people management section includes promotion criteria, pay and bonuses, and fixing or firing bad performers, where best practice is deemed the approach that gives strong rewards for those with both ability and effort.

Many other firm attributes are collected as part of the WMS, including information on employment, the fraction of employees with a degree and firm decentralisation. Decentralisation is assessed along four dimensions using the following questions: (i) "What agreement would your plant need from central head quarters to hire a full-time permanent shop floor worker?", (ii) "How much of sales and marketing is carried out at the plant level rather than at the central head quarters?" (iii) "Where are decisions taken on new product introductions - at the plant, at the central head quarters or at both?" and "What is the largest capital investment your plant could make without prior authorization from central head quarters?". As with management these are on a 1 to 5 scale, which we convert into a single decentralisation index by standardising each question, taking the average across questions and then re-standardising so that the final measure is mean-zero with a unit standard deviation.

Accounting Data

Data on firms' sales, employment, capital, materials and payroll (the wage bill), is drawn from Historical Orbis (HO) accounting data using the common company ID in the WMS and HO. Value added is calculated as sales minus materials. [20] Survival is measured as one for firms who are active and zero in the year they become inactive (we drop observations in the year after a firm exits).

20. Some firms report "costs of good sold" and not materials. In this case we estimate materials as costs of goods sold minus the wage bill.

Management-Accounting Panel Dataset

As described above, the data used in our analysis features a panel element. This is built by combining the WMS with the HO accounting panel data and the disaster information. Since management does not change much over time and the WMS is primarily repeated cross sections, we treat management, M_i as fixed over time by firm. When we have multiple observations on a single firm we simply average the responses.[21] In the main results, the only other WMS variable we use in the X_i controls is the skill variable (proportion of employees with a college degree). For this we linearly interpolate the data in the intervening years (results are robust to taking the simple average).

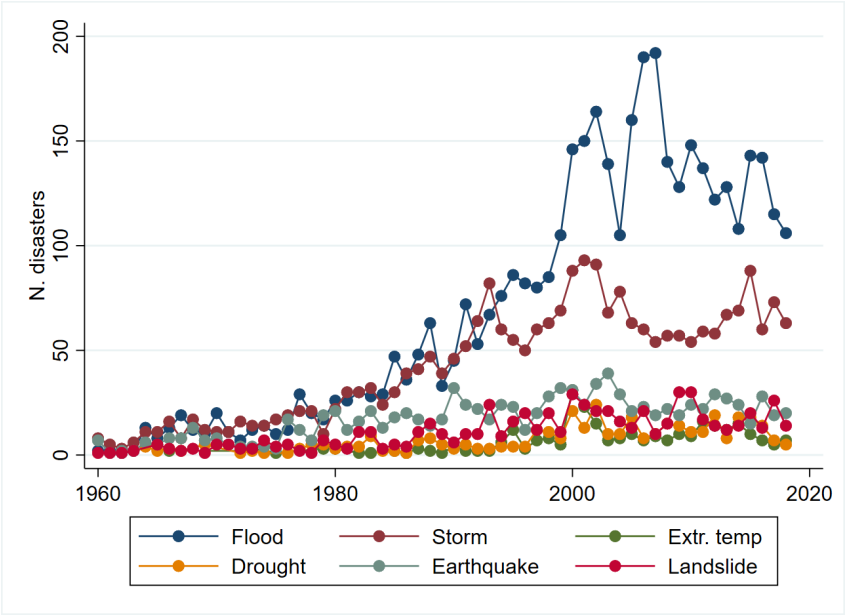
Matching to Natural Disasters Data

As described in the main text, we match the WMS-HO Management-Accounting dataset to natural disasters in GDIS by geocoding via the Google API. Figures A2 and A1 give some descriptives on the disasters recorded in GDIS.

The address used to geolocate firms relates to the plant that was interviewed for WMS respondents in 2015 or earlier. Respondents to the WMS in later years were not asked for the address of their plant and in these instances we therefore rely on address information from HO. Addresses in HO pertain to headquarters, which means we lack accurate location information for plants that belong to multi-site firms and that were surveyed by the WMS after 2015. We retain these in our main analysis sample under the assumption the gain in statistical power their inclusion affords is greater than the possible attenuation bias caused by inaccuracy of their location. In Appendix **??** we show our main results are qualitatively similar when analysis is restricted to an 'accurate location' subsample that disregards plants in multi-site firms surveyed in the WMS after 2015.

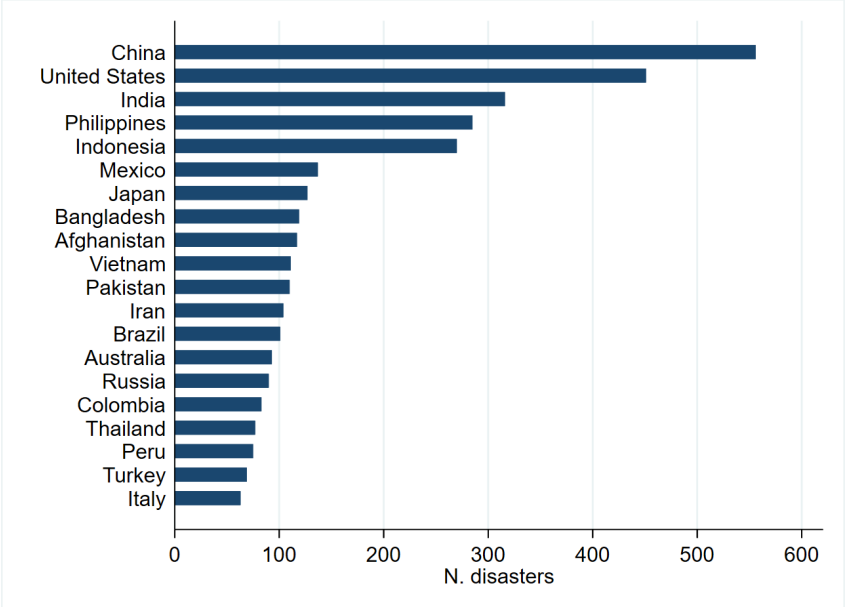
21. We treat the decentralisation measure in the same manner for this robustness test.

Figure A1: Natural Disasters Recorded in GDIS, by Type of Disaster



Note: figure shows the number of disasters per year recorded in GDIS by type.

Figure A2: Natural Disasters Recorded in GDIS Between 1995 and 2018, by Country



Note: figure shows the total count of disasters per country between 1995 and 2018 as the period covering the vast majority of the WMS-HO panel for which we have natural disaster data. Figure restricted to the 20 countries with the most natural disasters observed between 1995 and 2018.

Sample Coverage

The outcome of the match across all three datasets is a panel of 7,899 firms and 112,783 observations with the country breakdown given in Table A1. The comparison between the firms in the analysis sample and the full WMS is given in Table A2.

Table A1: Analysis Sample by Country

	(1) N Firms	(2) N Obs.	(3) High Income
Argentina	294	2372	No
Australia	293	3280	Yes
Brazil	708	6930	No
Canada	242	1807	Yes
Chile	285	2764	Yes
China	422	5572	No
Colombia	176	901	No
Ethiopia	5	30	No
France	365	7421	Yes
Germany	371	5595	Yes
Ghana	23	109	No
Greece	372	5800	Yes
India	396	5610	No
Ireland	83	1274	Yes
Italy	482	9735	Yes
Japan	87	1410	Yes
Kenya	32	32	No
Mexico	252	1877	No
Mozambique	14	64	No
New Zealand	58	633	Yes
Nicaragua	5	20	No
Nigeria	7	86	No
Poland	214	4205	Yes
Portugal	258	4781	Yes
Singapore	288	3636	Yes
Spain	249	5117	Yes
Sweden	181	3535	Yes
Tanzania	36	228	No
Turkey	264	2485	No
United Kingdom	844	17301	Yes
United States	517	7600	Yes
Vietnam	59	503	No
Zambia	17	70	No
Total	7899	112783	

Note: table shows the analysis sample by country, which comprises of firms from the WMS survey that we could match to the HO panel and accurately geocode using the procedure described in Section 2.

Table A2: Sample Characteristics

	(1) Full WMS	(2) Analysis sample	(3) Non-sample	(4) Difference (2)-(3)
Management	0.03	0.04	-0.06	0.10 (0.00)
Decentralisation	-0.01	-0.01	0.00	-0.01 (0.45)
Employment	844	899	758	141 (0.01)
Workforce degree (%)	0.16	0.16	0.17	-0.01 (0.00)
Firm age (years)	45	45	46	-0.32 (0.72)
Africa (%)	0.05	0.01	0.11	-0.09 (0.00)
Asia (%)	0.16	0.14	0.20	-0.07 (0.00)
Europe (%)	0.40	0.50	0.24	0.26 (0.00)
Latin America (%)	0.23	0.23	0.24	-0.01 (0.08)
North America (%)	0.12	0.08	0.17	-0.08 (0.00)
Oceania (%)	0.04	0.03	0.04	-0.00 (0.26)
N firms	13721	7899	5822	

Note: parentheses in the right-most column contain p-values from a test that the means of the variable in a particular row are equal across sample and non-sample firms.

Table A3: Correlation Between Disaster Exposure and Management

	(1)	(2)
Management	0.003	0.002
	(0.002)	(0.002)
Expected Disaster Exposure		0.992***
		(0.011)
Year Dummies	YES	YES
Country Dummies	YES	YES
Industry Dummies	YES	YES
Firm Characteristics	YES	YES
N obs.	112783	112783
N firms	7899	7899

Note: dependent variable is D_{it}, which indicates whether firm i was within 40km of a disaster in year t. Standard errors in parentheses clustered at the firm level. */**/*** denote significance at the 10/5/1 percent level respectively.

B Supplementary Results

B.1 Misclassification of Disaster Exposure

This section discusses how misclassification in our measure of firms' exposure to natural disasters affects estimation of disaster impacts and their interaction with management practices.

Setup. Let $D_{it}^* \in \{0, 1\}$ denote the true indicator that firm i is exposed to a disaster in year t, and let $D_{it} \in \{0, 1\}$ denote the observed indicator constructed from GDIS data using the

procedure described in Section 2. Consider the structural relationship

$$Y_{it} = \beta_D D^*_{it} + \beta_M M_i + \beta_{DM} \left(D^*_{it} \times M_i\right) + X'_{it}\gamma + \varepsilon_{it}, \tag{7}$$

where M_i denotes management quality, X_{it} collects additional controls and fixed effects, and ε_{it} is an unobserved error term satisfying $\mathbb{E}[\varepsilon_{it} \mid D^*_{it}, M_i, X_{it}] = 0$.

Because D_{it} is binary, measurement error takes the form of *misclassification*. Define the false-positive and false-negative rates as

$$\alpha_{it} \equiv \Pr(D_{it} = 1 \mid D^*_{it} = 0, X_{it}), \quad \text{(false positives)} \tag{8}$$

$$\beta_{it} \equiv \Pr(D_{it} = 0 \mid D^*_{it} = 1, X_{it}), \quad \text{(false negatives)}. \tag{9}$$

A convenient representation decomposes the observed indicator into its conditional mean and a mean-zero residual:

$$D_{it} = \mathbb{E}[D_{it} \mid D^*_{it}, X_{it}] + u_{it}, \qquad \text{with} \qquad \mathbb{E}[u_{it} \mid D^*_{it}, X_{it}] = 0. \tag{10}$$

Using (8)–(9), the conditional mean is

$$\mathbb{E}[D_{it} \mid D^*_{it}, X_{it}] = \alpha_{it} + (1 - \alpha_{it} - \beta_{it})\, D^*_{it}. \tag{11}$$

Classical misclassification. We first consider a setting in which misclassification is *stable conditional on observable controls*. Specifically, assume:

(A1) **Conditional stability:** $\alpha_{it} = \alpha(X_{it})$ and $\beta_{it} = \beta(X_{it})$.

(A2) **Nondifferential misclassification:** $\mathbb{E}[u_{it} \mid D^*_{it}, M_i, X_{it}] = 0$, i.e., conditional on true exposure and observables, classification errors are mean independent of management.

(A3) **Exogeneity of true exposure:** $\mathbb{E}[\varepsilon_{it} \mid D^*_{it}, M_i, X_{it}] = 0$.

(A4) **Better-than-random classification:** $\alpha_{it} + \beta_{it} < 1$ almost surely.

Under (A1) and (A4), define $\lambda_{it} \equiv 1 - \alpha_{it} - \beta_{it} \in (0, 1]$, so that

$$D_{it} = \alpha_{it} + \lambda_{it} D^*_{it} + u_{it}. \tag{12}$$

Conditional on X_{it}, D_{it} is therefore a noisy, affine transformation of D^*_{it}, with the signal component scaled by $\lambda_{it} < 1$. Replacing D^*_{it} with D_{it} thus injects additional noise into both the disaster indicator and its interaction with management, while preserving mean independence from the outcome error under (A2)–(A3). As a result, estimation using D_{it} attenuates the coefficients on the disaster main effect and the disaster–management interaction toward zero.

Misclassification correlated with management. Attenuation need not hold if misclassification rates vary systematically with management quality. Suppose instead that

$$\alpha_{it} = \alpha(M_i, X_{it}), \qquad \beta_{it} = \beta(M_i, X_{it}), \qquad \lambda_{it} = 1 - \alpha_{it} - \beta_{it}.$$

Then the conditional mean of the observed indicator depends on management,

$$\mathbb{E}[D_{it} \mid D^*_{it}, M_i, X_{it}] = \alpha_{it} + \lambda_{it} D^*_{it},$$

so D_{it} is no longer a proxy for D^*_{it} with a management-invariant measurement process. In this case, the covariance between observed and true disaster exposure, which identifies the disaster coefficient, includes additional terms arising from the joint dependence of misclassification rates and exposure on management, and therefore need not imply attenuation. The same logic applies to the interaction regressor $D_{it} \times M_i$: when misclassification varies with management, management-related components of the classification error enter directly into the interaction, and the resulting covariance terms can be positive or negative.

Suppose, for example, the true interaction effect is linear in management, with better management mitigating (but not completely offsetting) the negative impact of disasters. If false negatives are more common among high-management firms, then some well-managed but truly exposed firms are misclassified as unexposed with unusually low outcomes. This can induce a negative association between outcomes and management among firms classified as unexposed, biasing the linear management effect downward and potentially distorting the estimated interaction either upward (by shifting explanatory power from the management main effect to the disaster–management interaction) or downward (by reducing the variation in management among firms classified as exposed, which weakens identification of the interaction).

Empirical Assessment. To gauge the magnitude of misclassification in our measure of disaster exposure, we draw on the Global Active Archive of Large Flood Events (GAALFE) maintained by the Dartmouth Flood Observatory (Brakenridge 2025). The GAALFE begins in 1985 and aims to provide a globally comprehensive record of major flood events. Floods recorded prior to 2000 were compiled by DFO researchers from curated news reports, governmental sources, and humanitarian agency records, supplemented where possible by early satellite-based indications of surface water extent. Since 2000, the operation of the MODIS instruments aboard NASA's Terra and Aqua satellites has substantially improved the remote detection of inundation, increasing the role of satellite-derived flood mapping in the GAALFE compilation process. Because the GAALFE is constructed using different source material and greater reliance on remote sensing than GDIS, it provides an independent benchmark for evaluating flood coverage in our baseline data.

To quantify the magnitude of misclassification, we use the GAALFE to measure *false negatives* in the GDIS data. We focus on false negatives because the GAALFE targets large and persistent flood events that are readily detectable by satellite imagery, whereas GDIS is based on official disaster declarations. As a result, there are plausible reasons for floods to appear in GDIS but not in GAALFE. Conversely, it is difficult to explain why large inundation events of the type recorded in GAALFE would fail to meet the inclusion thresholds of GDIS.

Restricting attention to countries and years in our sample, we compare country-years in which floods are recorded in GAALFE to those in which floods are recorded in GDIS. Of the 2,554 flood events recorded in GAALFE over our sample period, 2,309 align with flood events recorded in GDIS, implying an aggregate false negative rate of approximately 10%. While false

negatives thus appear limited on average, there is substantial heterogeneity across countries and over time. Between 1985 and 1999, for example, GAALFE records seven flood-years in the UK, of which four do not appear in GDIS (a false negative rate of 57%), whereas all three GAALFE flood-years in New Zealand over this period are recorded in GDIS. Between 2000 and 2018, the UK false negative rate falls to 35% (six out of seventeen flood-years absent from GDIS), while the New Zealand false negative rate rises to 47% (seven out of fifteen flood-years absent from GDIS).

As discussed above, misclassification will attenuate estimates of disaster effects and the mediating role of management if misclassification is independent of management. If misclassification instead varies systematically with management, estimated coefficients may be biased upward or downward. To examine whether false negatives are correlated with management practices, we identify 'missing floods' as GAALFE flood events occurring in country-years with no corresponding flood recorded in GDIS. We merge these events with our firm-level panel and use GAALFE coordinates to classify firms as exposed to a missing flood if they are located within 40 km of the flood centroid. We then regress indicators of missing flood exposure on firm characteristics, estimating equations of the form

$$MF_{it} = \beta M_{it} + FE_{it} + \epsilon_{it}, \tag{13}$$

where MF_{it} is a binary indicator for exposure to a missing flood, M_{it} denotes management characteristics, and FE_{it} is a vector of fixed effects, which we vary in different specifications.

Of the 8204 firms in our sample, 426 are exposed to a missing flood. Table B4 contains estimates of the β parameters of equation (13), which reflect whether these firms are systematically different than other firms with respect to their management practices. Columns (1)–(2) show a small but statistically significant association between missing floods and management in specifications with no or only year fixed effects (the coefficients and standard errors are multiplied by 100 to ease exposition). Columns (3)–(4), however, show that this association disappears once country fixed effects are included, indicating that systematic variation in flood coverage in GDIS is driven entirely by country-level differences. Conditional on country and year dummies, misclassification therefore appears unrelated to management quality, implying that any bias from misclassification will attenuate our estimates toward zero rather than spuriously inflate them.

While this exercise is limited in that it only pertains to false negatives of flood events, floods are the most common event in the GDIS and false negatives are plausibly more relevant than false positives. Taken together, the results in Table B4 provide reassuring evidence that any remaining misclassification in disaster exposure is unlikely to generate upward bias in our estimated disaster effects or their interaction with management.

Table B4: Missing Floods and Management Characteristics

	(1)	(2)	(3)	(4)
Management	0.080***	0.070***	0.020	0.017
	(0.018)	(0.018)	(0.015)	(0.015)
Year Dummies	No	Yes	No	Yes
Country Dummies	No	No	Yes	Yes
N obs.	112783	112783	112783	112783
N firms	7899	7899	7899	7899

Note: outcome variable is a binary indicator that takes the value of 1 if a firm is within 40km of a missing flood and zero otherwise. Standard errors in parentheses clustered at the firm level. Coefficients and standard errors are multiplied by 100. */**/*** denote significance at the 10/5/1 percent level respectively.

B.2 Testing for the Impact of Disasters on Management Practices

Our interpretation of the interaction term between disaster exposure and management practices in equation (3), as capturing the extent to which management practices mediate the impact of disasters on firm performance, relies on the assumption that disaster exposure does not itself induce changes in management practices. If disasters systematically altered management, particularly in ways correlated with firm growth, then the interaction coefficient could reflect endogenous managerial responses.

To assess the plausibility of this assumption, we exploit the panel structure of the WMS and focus on the subsample of firms observed in at least two survey waves. We estimate specifications of the form

$$M_{it}^{(2)} = \beta_0 + \beta_1 M_i^{(1)} + \beta_2 D_i^{(1)-(2)} + \tau_t + \iota_i + \epsilon_{it}, \tag{14}$$

where $M_i^{(1)}$ denotes firm i's management score in the earlier wave they are sampled in the WMS and $M_{it}^{(2)}$ the management score in the subsequent WMS wave. The indicator $D_i^{(1)-(2)}$ equals one if firm i is exposed to at least one disaster between its first and second WMS observation and τ_t and ι_i are time and country fixed effects, respectively. Our maintained hypothes is that $\beta_2 = 0$, namely that management practices do not respond to disasters.

Because our main outcome variables are expressed as growth rates, a related concern is that disasters may affect management differently for firms on different growth trajectories. Such heterogeneous responses would complicate the interpretation of the interaction term in equation (3). To examine this possibility, we estimate an augmented specification:

$$M_{it}^{(2)} = \beta_0 + \beta_1 M_i^{(1)} + \beta_2 D_i^{(1)-(2)} + \beta_3 \left(D_i^{(1)-(2)} \times g_i^{(1)-(2)} \right) + \beta_x X_{it} + \epsilon_{it}, \tag{15}$$

where $g_i^{(1)-(2)}$ measures firm i's employment growth in the last pre-disaster year prior to any disaster occurring between WMS waves (1) and (2).

Table B5 reports estimates from equation (14) in column (1) and from equation (15) in column (2). Across both specifications, management scores exhibit substantial persistence, while neither disaster exposure nor its interaction with firm growth is associated with statistically or economically meaningful changes in management practices.

Table B5: Testing for Impact of Disaster Exposure on Management Practices

	(1)	(2)
Previous Management	0.409***	0.350***
	(0.016)	(0.023)
Any disaster between WMS years	-0.010	0.025
	(0.034)	(0.053)
Emp. Growth		0.298
		(0.198)
(Emp. Growth) * (Any disaster)		-0.376
		(0.313)
Year Dummies	YES	YES
Country Dummies	YES	YES
Industry Dummies	YES	YES
N	2752	1341

Note: dependent variable is firms' management score taken from the later WMS wave in which they are surveyed. Standard errors in parentheses clustered at the firm level. */**/*** denote significance at the 10/5/1 percent level respectively.

B.3 Additional Disaster Impact Estimates

Table B6: Impact of Disaster Exposure on 1-year Firm Performance: Profits and Productivity

	(1)	(2)	(3)
	Log differences $(t, t+1)$		
	EBIT	ROCE	TFP
Panel A: Linear Management			
Management	0.0031	0.0090***	0.0020*
	(0.0028)	(0.0024)	(0.0011)
Panel B: Linear Disaster Exposure			
Disaster in year	-0.0084	-0.0130*	-0.0036
	(0.0089)	(0.0075)	(0.0037)
Panel C: Linear Firm Characteristics			
Disaster in year	-0.0071	-0.0131*	-0.0035
	(0.0089)	(0.0076)	(0.0037)
Management	0.0066**	0.0099***	0.0013
	(0.0030)	(0.0026)	(0.0012)
Panel D: Linear Firm Characteristics and Management-Disaster interaction			
Disaster in year	-0.0072	-0.0130*	-0.0035
	(0.0089)	(0.0076)	(0.0037)
Management	0.0069**	0.0093***	0.0015
	(0.0034)	(0.0030)	(0.0015)
(Management)* (Disaster)	-0.0016	0.0031	-0.0010
	(0.0087)	(0.0074)	(0.0039)
Panel E: Linear Firm Characteristics and Full Disaster interactions			
Disaster in year	-0.0071	-0.0129*	-0.0037
	(0.0089)	(0.0076)	(0.0037)
Management	0.0063*	0.0094***	0.0015
	(0.0034)	(0.0030)	(0.0015)
(Management)* (Disaster)	0.0013	0.0027	-0.0011
	(0.0090)	(0.0077)	(0.0041)
Dep. var. mean	0.058	-0.037	0.006
N obs.	52840	46200	25325
N firms	5019	4273	2106

Note: standard errors in parentheses clustered at the firm level. Differences in sample size across columns are due to missing values in the HO financial data. Dependent variable in columns (1)-(3) are one-year differences in the log of the outcome denoted in the column title defined according to equation (1). "EBIT" is the HO "profit before tax" variable, "ROCE" is the HO "ROCE using net income" variable. "TFP" stands for total factor productivity, which we calculate as the residual from a value-added production function estimated for each 2-digit industry via the control function approach of Ackerberg et al. (2015). */**/*** denote significance at the 10/5/1 percent level respectively.

Table B7: Impact of Disaster Exposure on Capital Growth

	(1)	(2)	(3)	(4)
Disaster exposure (t)	-0.004*	-0.004	-0.004*	-0.005*
	(0.002)	(0.002)	(0.002)	(0.002)
Disaster exposure (t-1)		-0.003	-0.003	-0.002
		(0.002)	(0.002)	(0.002)
Disaster exposure (t-2)			0.001	0.002
			(0.002)	(0.002)
Disaster exposure (t-3)				-0.006**
				(0.002)
Disaster (t) × Management	0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.003)
Disaster (t-1) × Management		0.008***	0.008***	0.008***
		(0.003)	(0.003)	(0.003)
Disaster (t-2) × Management			0.001	0.000
			(0.002)	(0.002)
Disaster (t-3) × Management				0.001
				(0.003)
Management (centered)	0.001	0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
N obs.	73869	69974	66073	62035
N firms	5288	5216	5163	5113

Note: dependent variable is one-year-ahead difference in log capital. Table shows coefficient estimates similar to those of Table 1 but including an expanded set of disaster exposure lags and their interaction with management. Similarly to Panel E of Table 1, all columns additionally interact the lagged disaster indicators with firm characteristics. Standard errors in parentheses clustered at the firm level. */**/*** denote significance at the 10/5/1 percent level respectively.

Table B8: Impact of Disaster Exposure on Employment Growth

	(1)	(2)	(3)	(4)
Disaster exposure (t)	-0.002*	-0.003*	-0.003*	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Disaster exposure (t-1)		-0.001	-0.001	-0.001
		(0.001)	(0.001)	(0.001)
Disaster exposure (t-2)			-0.001	-0.001
			(0.001)	(0.001)
Disaster exposure (t-3)				-0.001
				(0.001)
Disaster (t) × Management	0.003*	0.003*	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Disaster (t-1) × Management		0.000	-0.000	-0.000
		(0.002)	(0.002)	(0.002)
Disaster (t-2) × Management			0.001	0.001
			(0.002)	(0.002)
Disaster (t-3) × Management				0.000
				(0.002)
Management (centered)	0.001	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
N obs.	59487	56836	54062	51017
N firms	4706	4612	4543	4448

Note: same as note to Table B7 except that dependent variable is one-year-ahead difference in log employment.

Table B9: Impact of Disaster Exposure on Value Added Growth

	(1)	(2)	(3)	(4)
Disaster exposure (t)	-0.008***	-0.009***	-0.009***	-0.009***
	(0.003)	(0.003)	(0.003)	(0.003)
Disaster exposure (t-1)		-0.002	-0.002	-0.003
		(0.003)	(0.003)	(0.003)
Disaster exposure (t-2)			0.002	0.002
			(0.003)	(0.003)
Disaster exposure (t-3)				0.004
				(0.003)
Disaster (t) × Management	0.004	0.004	0.004	0.005
	(0.003)	(0.003)	(0.004)	(0.004)
Disaster (t-1) × Management		0.001	0.000	-0.000
		(0.004)	(0.004)	(0.004)
Disaster (t-2) × Management			-0.003	-0.002
			(0.004)	(0.004)
Disaster (t-3) × Management				0.001
				(0.004)
Management (centered)	0.006***	0.005***	0.006***	0.005***
	(0.001)	(0.002)	(0.002)	(0.002)
N obs.	33700	32318	30858	29262
N firms	2580	2556	2539	2505

Note: same as note to Table B7 except that dependent variable is one-year-ahead difference in log value added.

Table B10: Impact of Disaster Exposure on Survival Probability

	(1)	(2)	(3)	(4)
Disaster exposure (t)	-0.005***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Disaster exposure (t-1)		0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)
Disaster exposure (t-2)			-0.002**	-0.003***
			(0.001)	(0.001)
Disaster exposure (t-3)				0.003***
				(0.001)
Disaster (t) × Management	0.003**	0.001	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Disaster (t-1) × Management		-0.001	-0.001	-0.001
		(0.001)	(0.001)	(0.001)
Disaster (t-2) × Management			0.001	0.001
			(0.001)	(0.001)
Disaster (t-3) × Management				-0.002
				(0.001)
Management (centered)	0.000	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
N obs.	112783	104884	97408	89963
N firms	7899	7476	7445	7391

Note: same as note to Table B7 except that dependent variable is a dummy variable that takes the value of one if the firm is observed in the following period.

Table B11: Impact of Disaster Exposure on 1-year Firm Performance: Heterogeneity by Country Income

	(1)	(2)	(3)	(4)
	Log differences $(t, t+1)$			
	Capital	Emp.	VA	Survival
Panel D: Linear Firm Characteristics and Management/High-income-Disaster interaction				
Management	-0.0010	0.0030	-0.0079	0.0194
	(0.0036)	(0.0035)	(0.0063)	(0.0123)
(Management)* (High-income)	0.0028	-0.0021	0.0143**	-0.0200
	(0.0038)	(0.0036)	(0.0065)	(0.0136)
Disaster in year	-0.0047	-0.0015	-0.0053	0.0346
	(0.0079)	(0.0073)	(0.0173)	(0.0261)
(Disaster)* (High-income)	0.0005	-0.0011	-0.0034	-0.0806***
	(0.0081)	(0.0073)	(0.0175)	(0.0286)
(Management)* (Disaster)	0.0116	0.0062	0.0194	0.1092***
	(0.0081)	(0.0079)	(0.0134)	(0.0276)
(Management)* (Disaster)* (High-income)	-0.0120	-0.0025	-0.0161	-0.1030***
	(0.0085)	(0.0080)	(0.0138)	(0.0304)
Panel E: Linear Firm Characteristics and Full Disaster interactions				
Management	-0.0011	0.0047	-0.0072	0.0188
	(0.0036)	(0.0035)	(0.0064)	(0.0123)
(Management)* (High-income)	0.0030	-0.0037	0.0136**	-0.0204
	(0.0038)	(0.0037)	(0.0065)	(0.0137)
Disaster in year	-0.0034	-0.0049	0.1473*	0.0648
	(0.0142)	(0.0107)	(0.0797)	(0.0573)
(Disaster)* (High-income)	-0.0003	0.0023	-0.1553*	-0.1324**
	(0.0144)	(0.0107)	(0.0797)	(0.0582)
(Management)* (Disaster)	0.0117	-0.0024	0.0171	0.1106***
	(0.0078)	(0.0092)	(0.0139)	(0.0290)
(Management)* (Disaster)* (High-income)	-0.0127	0.0055	-0.0135	-0.1002***
	(0.0082)	(0.0093)	(0.0142)	(0.0320)
Dep. var. mean	0.026	0.006	0.033	0.982
N obs.	73869	59487	33700	112783
N firms	5288	4706	2580	7899

Note: same as note to Table 1. High-income is defined using the 2018 World Bank income groups (World Bank 2023) and shown in Table A1. The linear high-income term is not included as it is perfectly collinear with the country dummies.

Table B12: Impact of Disaster Exposure on 1-year Firm Performance: Heterogeneity by Severity of Disasters

	(1)	(2)	(3)	(4)
	Log differences $(t, t+1)$			
	Capital	Emp.	VA	Survival
Panel D: Linear Firm Characteristics and Management-Disaster interaction				
Disaster in year	0.0038	-0.0010	-0.0092**	-0.0376***
	(0.0027)	(0.0016)	(0.0037)	(0.0145)
Severe Disaster in year	-0.0185***	-0.0038	0.0018	-0.0208
	(0.0039)	(0.0024)	(0.0054)	(0.0195)
Management	0.0014	0.0010	0.0056***	0.0031
	(0.0012)	(0.0009)	(0.0015)	(0.0054)
(Management)* (Disaster)	-0.0004	0.0012	0.0039	0.0007
	(0.0030)	(0.0017)	(0.0039)	(0.0157)
(Management)* (Sev. Disaster)	0.0030	0.0065**	0.0008	0.0663***
	(0.0042)	(0.0026)	(0.0054)	(0.0215)
Panel E: Linear Firm Characteristics and Full Disaster interactions				
Disaster in year	0.0044	-0.0009	-0.0081**	-0.0368**
	(0.0028)	(0.0017)	(0.0038)	(0.0146)
Severe Disaster in year	-0.0202***	-0.0031	0.0021	-0.0108
	(0.0040)	(0.0025)	(0.0055)	(0.0194)
Management	0.0015	0.0012	0.0055***	0.0031
	(0.0012)	(0.0009)	(0.0015)	(0.0054)
(Management)* (Disaster)	0.0002	0.0004	0.0039	0.0015
	(0.0032)	(0.0018)	(0.0042)	(0.0166)
(Management)* (Sev. Disaster)	0.0010	0.0059**	0.0011	0.0652***
	(0.0045)	(0.0028)	(0.0058)	(0.0226)
Dep. var. mean	0.026	0.006	0.033	0.982
N obs.	73869	59487	33700	112783
N firms	5288	4706	2580	7899

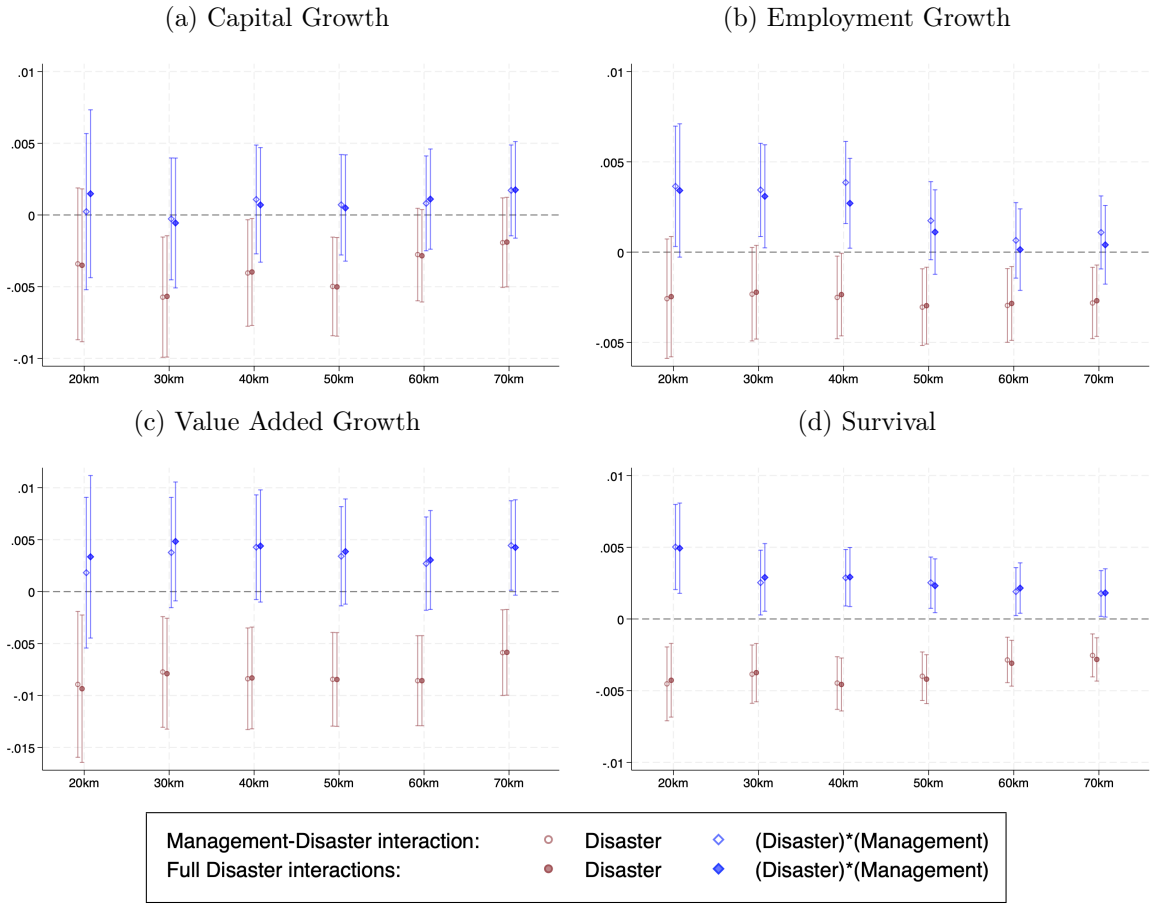
Note: same as note to Table 1.

Table B13: Impact of Disaster Exposure and Management Components on 1-year Firm Performance

	(1)	(2)	(3)	(4)
	Log differences $(t, t+1)$			
	Capital	Emp.	VA	Survival
Panel E: Linear Firm Characteristics and Full Disaster interactions				
Disaster in year	-0.0040*	-0.0023*	-0.0084***	-0.0457***
	(0.0023)	(0.0014)	(0.0030)	(0.0112)
Operations	0.0013	0.0021*	0.0027	0.0217***
	(0.0016)	(0.0011)	(0.0019)	(0.0069)
Monitoring	-0.0043**	-0.0042***	0.0026	-0.0186**
	(0.0020)	(0.0013)	(0.0023)	(0.0082)
Targets	-0.0000	-0.0011	-0.0050**	0.0007
	(0.0018)	(0.0013)	(0.0022)	(0.0081)
People	0.0051***	0.0053***	0.0063***	0.0046
	(0.0015)	(0.0011)	(0.0019)	(0.0069)
(Operations)* (Disaster)	-0.0044	-0.0016	-0.0036	0.0076
	(0.0031)	(0.0019)	(0.0040)	(0.0166)
(Monitoring)* (Disaster)	0.0063*	0.0022	-0.0010	-0.0167
	(0.0036)	(0.0023)	(0.0045)	(0.0200)
(Targets)* (Disaster)	-0.0006	0.0043**	0.0123**	0.0375*
	(0.0038)	(0.0022)	(0.0050)	(0.0195)
(People)* (Disaster)	-0.0017	-0.0023	-0.0027	0.0069
	(0.0032)	(0.0019)	(0.0044)	(0.0173)
Dep. var. mean	0.026	0.006	0.033	0.982
N obs.	73869	59487	33700	112783
N firms	5288	4706	2580	7899

Note: same as note to Table 1.

Figure B3: Main Parameter Estimates by Disaster Exposure Distance Threshold



Note: figure shows estimates of the β_0 and β_4 parameters from equation (3) obtained when disaster exposure is defined using various distance thresholds, indicated by the x-axis labels. Maroon circles represent the β_0 disaster effect, while blue diamonds represent the β_4 coefficient on the interaction of management practices with disaster exposure. The hollow markers that are slightly offset to the left show estimates from a specification where only management is interacted with disaster exposure (equivalent to panel D of Table 1), while the solid markers slightly offset to the right show estimates from a specification where all firm characteristics are interacted with disaster exposure (equivalent to panel E of Table 1). The dependent variable in panels (a) to (c) is the 1-year growth rate of the variable in the subfigure title and in panel (d) is a binary indicator for 1-period survival. Bars indicate 90% confidence intervals.

Table B14: Impact of Disaster Exposure, Management and Decentralisation on 1-year Firm Performance

	(1)	(2)	(3)	(4)
	Log differences $(t, t+1)$			
	Capital	Emp.	VA	Survival
Panel D: Linear Firm Characteristics and Management and Decentralisation-Disaster interaction				
Disaster in year	-0.0041*	-0.0025*	-0.0082***	-0.0443***
	(0.0023)	(0.0014)	(0.0030)	(0.0112)
Management	0.0014	0.0009	0.0055***	0.0032
	(0.0012)	(0.0009)	(0.0015)	(0.0054)
Decentralisation	0.0001	0.0034**	0.0016	0.0204**
	(0.0020)	(0.0014)	(0.0024)	(0.0085)
(Management)* (Disaster)	0.0012	0.0039***	0.0039	0.0277**
	(0.0023)	(0.0014)	(0.0031)	(0.0120)
(Decentralisation)* (Disaster)	-0.0023	-0.0006	0.0064	0.0160
	(0.0040)	(0.0024)	(0.0053)	(0.0197)
Panel E: Linear Firm Characteristics and Full Disaster interactions				
Disaster in year	-0.0040*	-0.0023*	-0.0082***	-0.0453***
	(0.0023)	(0.0014)	(0.0030)	(0.0112)
Management	0.0015	0.0011	0.0054***	0.0031
	(0.0012)	(0.0009)	(0.0015)	(0.0054)
Decentralisation	0.0000	0.0034**	0.0016	0.0204**
	(0.0020)	(0.0014)	(0.0024)	(0.0085)
(Management)* (Disaster)	0.0008	0.0027*	0.0041	0.0280**
	(0.0024)	(0.0015)	(0.0033)	(0.0126)
(Decentralisation)* (Disaster)	-0.0019	-0.0001	0.0060	0.0168
	(0.0040)	(0.0024)	(0.0053)	(0.0198)
Dep. var. mean	0.026	0.006	0.033	0.982
N obs.	73869	59487	33700	112783
N firms	5288	4706	2580	7899

Note: same as note to Table 1.

Table B15: Impact of Disaster Exposure on 1-year Firm Performance: Including Additional Year Fixed Effects

	(1)	(2)	(3)	(4)
	Log differences $(t, t+1)$			
	Capital	Emp.	VA	Survival
Panel A: Linear Management				
Management	0.0011	0.0013*	0.0030**	0.0145***
	(0.0011)	(0.0008)	(0.0013)	(0.0048)
Panel B: Linear Disaster Exposure				
Disaster in year	-0.0072***	-0.0031**	-0.0102***	-0.0292***
	(0.0023)	(0.0014)	(0.0030)	(0.0113)
Panel C: Linear Firm Characteristics				
Disaster in year	-0.0070***	-0.0028**	-0.0096***	-0.0326***
	(0.0023)	(0.0014)	(0.0030)	(0.0113)
Management	0.0016	0.0016*	0.0064***	0.0080
	(0.0011)	(0.0008)	(0.0014)	(0.0049)
Panel D: Linear Firm Characteristics and Management-Disaster interaction				
Disaster in year	-0.0069***	-0.0027*	-0.0096***	-0.0323***
	(0.0023)	(0.0014)	(0.0030)	(0.0113)
Management	0.0013	0.0009	0.0057***	0.0040
	(0.0012)	(0.0009)	(0.0015)	(0.0053)
(Management)* (Disaster)	0.0021	0.0039***	0.0038	0.0223*
	(0.0023)	(0.0014)	(0.0031)	(0.0119)
Panel E: Linear Firm Characteristics and Full Disaster interactions				
Disaster in year	-0.0067***	-0.0025*	-0.0094***	-0.0335***
	(0.0023)	(0.0014)	(0.0030)	(0.0114)
Management	0.0015	0.0011	0.0056***	0.0039
	(0.0012)	(0.0009)	(0.0015)	(0.0053)
(Management)* (Disaster)	0.0008	0.0028*	0.0041	0.0230*
	(0.0024)	(0.0015)	(0.0033)	(0.0124)
Dep. var. mean	0.026	0.006	0.033	0.982
N obs.	73869	59487	33700	112783
N firms	5288	4706	2580	7899

Note: same as note to Table 1 but controls include time fixed effects that differ by 1-digit industry and region in addition to 2-digit industry, year and country fixed effects. Regions are: Europe (including the UK); North America; Central and South America; Africa; Oceania and Asia.

Table B16: Impact of Disaster Exposure on 1-year Firm Performance: Including Additional Country and Industry-Specific Time Trends

	(1)	(2)	(3)	(4)
	Log differences $(t, t+1)$			
	Capital	Emp.	VA	Survival
Panel A: Linear Management				
Management	0.0011	0.0013*	0.0031**	0.0183***
	(0.0011)	(0.0008)	(0.0013)	(0.0048)
Panel B: Linear Disaster Exposure				
Disaster in year	-0.0048**	-0.0022	-0.0089***	-0.0439***
	(0.0022)	(0.0014)	(0.0030)	(0.0113)
Panel C: Linear Firm Characteristics				
Disaster in year	-0.0045**	-0.0020	-0.0086***	-0.0470***
	(0.0023)	(0.0014)	(0.0030)	(0.0113)
Management	0.0015	0.0017**	0.0064***	0.0113**
	(0.0011)	(0.0008)	(0.0014)	(0.0050)
Panel D: Linear Firm Characteristics and Management-Disaster interaction				
Disaster in year	-0.0045**	-0.0019	-0.0086***	-0.0467***
	(0.0023)	(0.0014)	(0.0030)	(0.0113)
Management	0.0012	0.0010	0.0056***	0.0064
	(0.0012)	(0.0009)	(0.0015)	(0.0054)
(Management)* (Disaster)	0.0013	0.0037***	0.0043	0.0273**
	(0.0023)	(0.0014)	(0.0031)	(0.0119)
Panel E: Linear Firm Characteristics and Full Disaster interactions				
Disaster in year	-0.0044*	-0.0018	-0.0085***	-0.0476***
	(0.0023)	(0.0014)	(0.0030)	(0.0113)
Management	0.0013	0.0012	0.0055***	0.0063
	(0.0012)	(0.0009)	(0.0015)	(0.0054)
(Management)* (Disaster)	0.0008	0.0026*	0.0046	0.0275**
	(0.0024)	(0.0015)	(0.0033)	(0.0125)
Dep. var. mean	0.026	0.006	0.033	0.982
N obs.	73869	59487	33700	112783
N firms	5288	4706	2580	7899

Note: same as note to Table 1 but additional controls include country time trends and two-digit industry.

Table B17: Impact of Disaster Exposure on 1-year Firm Performance: Disaster Survivor Sample

	(1)	(2)	(3)
	Log differences $(t, t+1)$		
	Capital	Emp.	VA
Panel A: Linear Management			
Management	0.0020*	0.0014*	0.0039***
	(0.0011)	(0.0008)	(0.0013)
Panel B: Linear Disaster Exposure			
Disaster in year	-0.0050**	-0.0026*	-0.0089***
	(0.0023)	(0.0014)	(0.0030)
Panel C: Linear Firm Characteristics			
Disaster in year	-0.0046**	-0.0021	-0.0086***
	(0.0023)	(0.0014)	(0.0030)
Management	0.0012	0.0013	0.0063***
	(0.0012)	(0.0008)	(0.0014)
Panel D: Linear Firm Characteristics and Management-Disaster interaction			
Disaster in year	-0.0045**	-0.0020	-0.0086***
	(0.0023)	(0.0014)	(0.0030)
Management	0.0011	0.0006	0.0055***
	(0.0013)	(0.0009)	(0.0015)
(Management)* (Disaster)	0.0004	0.0037***	0.0042
	(0.0023)	(0.0014)	(0.0031)
Panel E: Linear Firm Characteristics and Full Disaster interactions			
Disaster in year	-0.0045*	-0.0019	-0.0085***
	(0.0023)	(0.0014)	(0.0030)
Management	0.0012	0.0008	0.0053***
	(0.0013)	(0.0009)	(0.0015)
(Management)* (Disaster)	0.0002	0.0028*	0.0050
	(0.0025)	(0.0015)	(0.0033)
Dep. var. mean	0.025	0.007	0.033
N obs.	71553	57526	32755
N firms	5062	4486	2480

Note: same as note to Table 1 but sample is restricted to firms that do not exit our panel within one year of disaster exposure.

Table B18: Impact of Disaster Exposure on 1-year Firm Performance: Excluding Interpolated Skills

	(1)	(2)	(3)	(4)
	Log differences $(t, t+1)$			
	Capital	Emp.	VA	Survival
Panel A: Linear Management				
Management	0.0024**	0.0018**	0.0041***	0.0181***
	(0.0011)	(0.0008)	(0.0013)	(0.0047)
Panel B: Linear Disaster Exposure				
Disaster in year	-0.0046**	-0.0032**	-0.0088***	-0.0406***
	(0.0023)	(0.0014)	(0.0030)	(0.0112)
Panel C: Linear Firm Characteristics				
Disaster in year	-0.0041*	-0.0026*	-0.0084***	-0.0447***
	(0.0023)	(0.0014)	(0.0030)	(0.0112)
Management	0.0019*	0.0020**	0.0065***	0.0083*
	(0.0011)	(0.0008)	(0.0014)	(0.0050)
Panel D: Linear Firm Characteristics and Management-Disaster interaction				
Disaster in year	-0.0041*	-0.0025*	-0.0084***	-0.0443***
	(0.0023)	(0.0014)	(0.0030)	(0.0112)
Management	0.0017	0.0013	0.0057***	0.0032
	(0.0012)	(0.0009)	(0.0015)	(0.0053)
(Management)* (Disaster)	0.0012	0.0039***	0.0043	0.0282**
	(0.0023)	(0.0014)	(0.0031)	(0.0120)
Panel E: Linear Firm Characteristics and Full Disaster interactions				
Disaster in year	-0.0041*	-0.0024*	-0.0084***	-0.0461***
	(0.0023)	(0.0014)	(0.0030)	(0.0112)
Management	0.0017	0.0014	0.0055***	0.0029
	(0.0012)	(0.0009)	(0.0015)	(0.0054)
(Management)* (Disaster)	0.0010	0.0031**	0.0049	0.0297**
	(0.0024)	(0.0015)	(0.0033)	(0.0124)
Dep. var. mean	0.026	0.006	0.033	0.982
N obs.	73869	59487	33700	112783
N firms	5288	4706	2580	7899

Note: same as note to Table 1 but firm characteristic controls do not include share of employees with a degree.

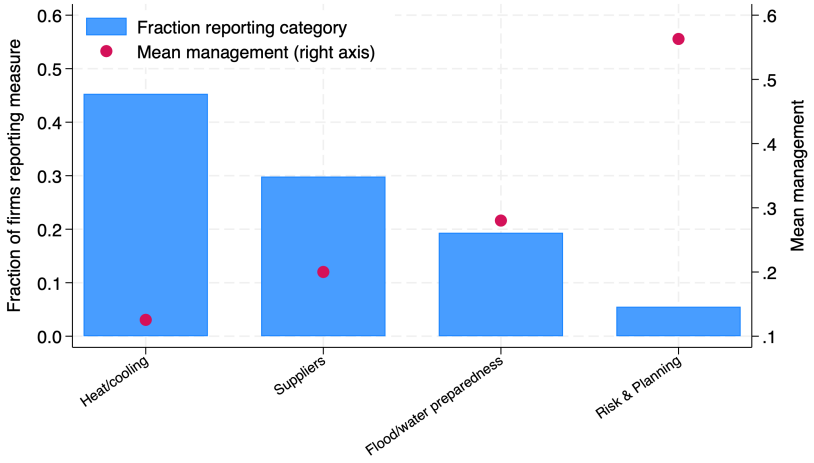
Table B19: Impact of Disaster Exposure on 1-year Firm Performance: Accurate Location Sample

	(1)	(2)	(3)	(4)
	Log differences $(t, t+1)$			
	Capital	Emp.	VA	Survival
Panel A: Linear Management				
Management	0.0024**	0.0019**	0.0046***	0.0170***
	(0.0011)	(0.0008)	(0.0014)	(0.0049)
Panel B: Linear Disaster Exposure				
Disaster in year	-0.0038	-0.0030**	-0.0095***	-0.0428***
	(0.0023)	(0.0014)	(0.0031)	(0.0117)
Panel C: Linear Firm Characteristics				
Disaster in year	-0.0034	-0.0024*	-0.0092***	-0.0475***
	(0.0023)	(0.0014)	(0.0031)	(0.0117)
Management	0.0012	0.0014	0.0062***	0.0072
	(0.0012)	(0.0009)	(0.0014)	(0.0052)
Panel D: Linear Firm Characteristics and Management-Disaster interaction				
Disaster in year	-0.0034	-0.0024*	-0.0093***	-0.0471***
	(0.0023)	(0.0014)	(0.0031)	(0.0117)
Management	0.0010	0.0007	0.0056***	0.0022
	(0.0013)	(0.0009)	(0.0015)	(0.0056)
(Management)* (Disaster)	0.0011	0.0038***	0.0031	0.0285**
	(0.0024)	(0.0014)	(0.0032)	(0.0124)
Panel E: Linear Firm Characteristics and Full Disaster interactions				
Disaster in year	-0.0033	-0.0023	-0.0092***	-0.0483***
	(0.0023)	(0.0014)	(0.0031)	(0.0117)
Management	0.0011	0.0009	0.0056***	0.0021
	(0.0013)	(0.0009)	(0.0016)	(0.0056)
(Management)* (Disaster)	0.0008	0.0028*	0.0027	0.0292**
	(0.0025)	(0.0015)	(0.0035)	(0.0130)
Dep. var. mean	0.025	0.005	0.031	0.981
N obs.	69860	56072	30567	108324
N firms	5040	4474	2385	7639

Note: same as note to Table 1 except that sample is restricted to accurate location sub-sample.

B.4 Climate Risk Perceptions and Climate Adaptation

Figure B4: Adaptation Categories Reported by Firms



Note: bars shows share of firms that reported any adaptation action by different categories of adaptation. Categories were inferred from WMS analyst notes based on keyword matches. Markers show the average management score among firms that report a given category.

Table B20: Examples of Adaptation Taken from WMS Analyst Notes

Adaptation Category	Example Analyst Notes
Heat/Cooling	• Humidity records review of warehouses to keep them at temperature. Installation of an air system in the winery. • They readapted the machines because with the increase in temperature it becomes a very hot environment. They inserted cooling systems.
Suppliers	• There are contingency plans in case natural disasters affect agricultural inputs. • Diversifying supply chain to not get hurt like they did 10 years ago with few suppliers closing down.
Flood/Water Preparedness	• Contingency plans for floods (they are near a river) with an emergency plan in case of need. • Water crisis worries them as they use a lot of water in their processes. They have optimized the water resources they use to use less and are implementing recycling processes.
Risk & Planning	• It has a contingency and sustainability plan for power failures and possible natural catastrophes due to the fires that broke out in Tondela a few years ago. • Contingency plans for floods (they are near a river) with an emergency plan in case of need.

Note: table contains examples of notes taken by WMS analysts when scoring firms against the climate adaptation question. Two examples are provided for each adaptation category.

Table B21: Perceptions of Climate Change Risk and Management: Floods and Storms

	(1)	(2)	(3)
Any Flood/Storm 2010-2018	0.054	0.032	0.036
	(0.070)	(0.069)	(0.069)
Management		0.096***	0.025
		(0.034)	(0.053)
(Management) * (Flood/Storm 2010-2018)			0.168**
			(0.070)
Any disaster 1970-1979	-0.223*	-0.254**	-0.244*
	(0.129)	(0.126)	(0.128)
(Management) * (Flood/Storm 1970-1979)			-0.226**
			(0.104)
N obs.	1117	1117	1117
Industry Dummies	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes
Linear Firm Characteristics	No	Yes	Yes
Firm Char.-Disaster Interactions	No	No	Yes

Note: same as note to Table 2.

Table B22: Perceptions of Climate Change Risk and Management: Earthquakes

	(1)	(2)	(3)
Any Earthquake 2010-2018	-0.162	-0.146	-0.157
	(0.127)	(0.123)	(0.127)
Management		0.093***	0.097**
		(0.035)	(0.038)
(Management) * (Earthquake 2010-2018)			-0.063
			(0.100)
Any disaster 1970-1979	0.148	0.112	0.118
	(0.182)	(0.179)	(0.181)
(Management) * (Earthquake 1970-1979)			0.117
			(0.175)
N obs.	1117	1117	1117
Industry Dummies	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes
Linear Firm Characteristics	No	Yes	Yes
Firm Char.-Disaster Interactions	No	No	Yes

Note: same as note to Table 2.

Table B23: Association Between Climate Risk Perceptions, Management Components and Disaster Exposure

	(1) Operations	(2) Monitoring	(3) Targets	(4) People
Any disaster 2010-2018	-0.004	-0.008	0.014	0.009
	(0.080)	(0.080)	(0.079)	(0.081)
Mgmt. Component	0.011	0.006	-0.016	0.011
	(0.052)	(0.050)	(0.056)	(0.056)
(Mgmt. Component) * (Disaster 2010-2018)	0.124*	0.094	0.228***	0.184**
	(0.072)	(0.067)	(0.075)	(0.073)
Any disaster 1970-1979	-0.210**	-0.207**	-0.203*	-0.202*
	(0.104)	(0.105)	(0.104)	(0.103)
(Mgmt. Component) * (Disaster 1970-1979)	-0.158	-0.145*	-0.224**	-0.126
	(0.103)	(0.088)	(0.093)	(0.085)
N obs.	1117	1117	1117	1117
Industry Dummies	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes
Linear Firm Characteristics	Yes	Yes	Yes	Yes
Firm Char.-Disaster Interactions	Yes	Yes	Yes	Yes

Note: same as note to Table 2 except that 'Mgmt. Component' pertains to the specific management component denoted in the column title.

Table B24: Climate Adaptation and Management: Floods and Storms

	(1)	(2)	(3)	(4)	(5)
Any Flood/Storm 2010-2018	0.126*	0.102	0.092	0.094	0.082
	(0.068)	(0.067)	(0.067)	(0.067)	(0.066)
Management	0.307***	0.271***	0.265***	0.227***	0.240***
	(0.032)	(0.032)	(0.032)	(0.050)	(0.049)
(Management) * (Flood/Storm 2010-2018)				0.040	0.034
				(0.066)	(0.064)
Risk perception		0.216***	0.220***	0.221***	0.220***
		(0.030)	(0.030)	(0.031)	(0.031)
(Management) * (Risk perception)			0.091***	0.089***	0.086***
			(0.030)	(0.030)	(0.030)
N obs.	1117	1117	1117	1117	1117
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes	Yes
1970s Disasters	Yes	Yes	Yes	Yes	Yes
Linear Firm Characteristics	No	Yes	Yes	Yes	Yes
Firm Char.-Disaster Interactions	No	No	No	No	Yes

Note: same as note to Table 3.

Table B25: Climate Adaptation and Management: Earthquakes

	(1)	(2)	(3)	(4)	(5)
Any Earthquake 2010-2018	0.039	0.065	0.062	0.062	0.055
	(0.129)	(0.130)	(0.129)	(0.128)	(0.126)
Management	0.307***	0.270***	0.263***	0.268***	0.266***
	(0.033)	(0.032)	(0.032)	(0.035)	(0.035)
(Management) * (Earthquake 2010-2018)				-0.007	-0.082
				(0.095)	(0.101)
Risk perception		0.219***	0.223***	0.223***	0.226***
		(0.030)	(0.030)	(0.030)	(0.030)
(Management) * (Risk perception)			0.094***	0.094***	0.093***
			(0.030)	(0.030)	(0.030)
N obs.	1117	1117	1117	1117	1117
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes	Yes
1970s Disasters	Yes	Yes	Yes	Yes	Yes
Linear Firm Characteristics	No	Yes	Yes	Yes	Yes
Firm Char.-Disaster Interactions	No	No	No	No	Yes

Note: same as note to Table 3.

Table B26: Association Between Climate Change Adaptation, Management Components and Disaster Exposure

	(1) Operations	(2) Monitoring	(3) Targets	(4) People
Any disaster 2010-2018	0.118	0.120	0.113	0.134*
	(0.075)	(0.074)	(0.074)	(0.074)
Mgmt. Component	0.108**	0.153***	0.269***	0.160***
	(0.054)	(0.051)	(0.054)	(0.055)
(Mgmt. Component) * (Disaster 2010-2018)	0.007	0.024	-0.032	0.069
	(0.071)	(0.065)	(0.068)	(0.071)
Risk perception	0.232***	0.229***	0.219***	0.216***
	(0.031)	(0.031)	(0.031)	(0.031)
(Mgmt. Component) * (Risk perception)	0.098***	0.057**	0.053*	0.086***
	(0.032)	(0.028)	(0.029)	(0.030)
N obs.	1117	1117	1117	1117
Industry Dummies	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes
Linear Firm Characteristics	Yes	Yes	Yes	Yes
Firm Char.-Disaster Interactions	Yes	Yes	Yes	Yes

Note: same as note to Table 3 except that 'Mgmt. Component' pertains to the specific management component denoted in the column title.