NBER WORKING PAPER SERIES

DISASTER MANAGEMENT

Agnes Norris Keiller
John Van Reenen

Working Paper 32595
http://www.nber.org/papers/w32595

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2024

We would like to thank seminar participants in Stanford and LSE for helpful comments. Generous funding has come from ESRC/UKRI through the Programme On Innovation and Diffusion. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Disaster Management
Agnes Norris Keiller and John Van Reenen
NBER Working Paper No. 32595
June 2024
JEL No. Q54

ABSTRACT

Climate change is making natural disasters more frequent, yet little is known about the capacity of firms to withstand such disasters and adapt to their increased frequency. We examine this issue using a the latest wave of the World Management Survey (WMS) that includes new questions on firms' climate change perceptions and adaptation behavior. Combining this with geocoded data on natural disasters and previous WMS waves, we create a panel spanning 8,000 firms across 33 countries and three decades that shows exposure to disasters decreases growth inputs, outputs and firm survival. More importantly, firms with structured management practices are more resilient, suffering much smaller drops in jobs and capital. To understand the mechanisms behind this resilience, we use the new WMS climate questions to show better managed firms have more accurate perceptions of climate-related risks to their businesses. Such firms are also more likely to have implemented measures to adapt to climate change both overall and in response to their perceived climate risk. Other aspects of firm organisation, such as decentralisation, also help protect against disasters, but their adaptation behaviour is not well-targeted. These results show that improving management is one way to help protect economies from climate change shocks.

Agnes Norris Keiller
Department of Economics
London School of Economics
Houghton Street
WC2A 2AE
London, None WC2A 2AE
United Kingdom
A.Norris-Keiller@lse.ac.uk

John Van Reenen
Department of Economics
London School of Economics
Houghton Street
London, WC2A 2AE
United Kingdom
and NBER
j.vanreenen@lse.ac.uk

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 adapting to 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. This novel data combination spans 33 countries over 30 years from 1983 to 2018. Using this data, we show exposure to natural disasters decreases growth in capital, employment and value added and increases the probability of exit. We find that structured management practices protect firms from some of these negative impacts with better-managed firms experiencing significantly smaller reductions in jobs and capital following a disaster.

Exploiting novel questions in the latest WMS survey wave, we consider two potential channels through which management can reduce exposure to climate-related risks. We first consider the accuracy of managers' risk perceptions, showing firms with good management practices are more likely to perceive natural disasters as a risk to their business if they are located in an area that has experienced a disaster over recent years, suggesting they have more accurate perceptions of the risks they face. Second, we show well-managed firms are both more likely to act on their climate risk perceptions by implementing measures to adapt to climate change and are more likely to have undertaken adaptive measures conditional on their perceptions of climate risk. This 'adaptation gap' suggests the relationship between management practices and environmental resilience may increase as the effects of climate change become more pronounced.

We also look an another aspect of firm organisation, the decentralisation of decision making between headquarters and local establishments. Although decentralised firms are also more robust to disasters, they are more likely to regard climate change as a risk to their business regardless of location. While we observe a positive association between decentralisation and adaptation, this disappears when one controls for risk perceptions suggesting their higher risk perceptions are the principal reason they have adopted measures to reduce the impact of disasters and other aspects of climate change on their business.

Our findings contribute to three distinct literatures. First, we add to literature on the economic impacts of natural disasters by showing that management practices are an important dimension of heterogeneity. An extensive literature has examined the impacts of extreme weather and disasters on a range of outcomes including aggregate economic activity at the country level (Dell et al. 2012; Acevedo et al. 2020), and at the local level (Kocornik-Mina et al. 2020; Elliott et al. 2015). More specifically, our work is situated among a number of papers that analyse the impacts of environmental events on firm-level performance. Zhang et al. (2018), for example, use detailed production data on Chinese manufacturing firms to examine the impact of temperature on firm outcomes. They find an inverted-U relationship between temperature and productivity, with high temperatures having particularly large negative effects. Somanathan et al. (2021) also focus on temperature fluctuations and find a one-degree Celsius temperature rise leads to a 2% decrease in annual output among Indian manufacturing firms, principally due to the impact of temperature on labour. Most recently Clò et al. (2024) examine the impact of floods and landslides on Italian firms, finding that exposure to these events increases firm exit and decreases sales and employment conditional on survival, particularly among small and low-tech 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 have on firms that are themselves exposed to such disasters.[1] Given the consistent evidence of indirect impacts provided by these papers, our omission of such propagation effects means our findings shouldn't 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.

Second, we contribute to a literature examining the importance of management practices to 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.[2] However, relatively little is known about why management matters so much and there is ambiguity over what sort of practices matter. For example Aghion et al. (2021), find that more decentralised firms performed better throughout the negative shocks of the financial crisis whereas Lamorgese et al. (2024) and Li et al. (2023) find that firms with good overall management practices were more resilient during the COVID-19 pandemic. Our work finds that firms with good management practices are more resilient to negative environmental shocks, whereas those with decentralised decision making are less likely to exit. Examining the relationship between these aspects of management and climate-

1. As explained in section 2, our measure of 'exposure' is defined as being located within a 60km 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.

2. See Scur et al. (2021) for a recent survey using 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); Lazear et al. (2015).

related firm actions, we find management practices are associated with more accurate perceptions of climate-related risk and the adoption of measures to reduce firms' exposure to these risks, suggesting gaps in performance between well- and badly-managed firms may increase in coming years as climate change increases the frequency of natural disasters. The greater accuracy of well-managed firms' risk perceptions is consistent with Bloom et al. (2022), 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. While existing literature has emphasised how 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) environment, which can threaten firms' operations. Decentralised firms, meanwhile, do not necessarily have more accurate perceptions of disaster risk but rather are more likely to regard climate change as a risk to their business regardless of location, which appears the principal reason we observe them taking more adaptive measures.

A number of papers within this body of work examine links between management and climate change. The majority of these papers focus on climate change mitigation (i.e. actions by firms to reduce their contributions to climate change), and consistently find a positive association between such actions and management practices. An early example of this work is Bloom et al. (2010), who measure management practices in over 300 manufacturing firms in the UK finding that better-managed firms are not only more productive overall 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 well-managed firms adopt modern manufacturing practices, which allow them to increase productivity by using energy more efficiently. Their 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 than other firms especially when they have a decentralised structure.

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 we are aware of is Adhvaryu et al. (2022) who show management reduces the negative impact of pollution shocks on productivity. Using detailed data on productivity, task assignments, and managerial characteristics within a large Indian garment firm, they find 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 1 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 compliment 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.

Finally, 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.

The remainder of this paper is as follows. Section 2 describes the data we use to measure firm management practices, outcomes and their exposure to natural disasters. 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 6 concludes.

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.

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 latest version of the World Management Survey (WMS). The WMS is an interview-based survey conducted by highly trained interviewers who engage middle managers in semi-structured conversations about the daily 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 14,623 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 have significant predictive power of a range of dimensions of establishment performance and organisational outcomes, with well-managed firms being more productive, more innovative and faster-growing (Scur et al. 2021). Our empirical analysis also considers the extent that decisions in a firm are decentralised, which the WMS measures with three questions regarding the amount of autonomy plant managers have over hiring, marketing and product introduction decisions.[3].

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. 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. 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?

We examine the association between management, exposure to natural disasters and standardised versions of these scores, which are henceforth referred to as 'Climate risk perception' and 'Climate adaptation' (Risk perception/Adaptation for short), respectively.

To measure firms' financial outcomes we combine the WMS with Historical Orbis (HO), to obtain a panel dataset containing a range of metrics such as employment, capital (fixed assets) and value added. Changes in company identifiers mean we are unable to match all WMS firms with an HO record and even among matched firms, financial information can be missing.[4] We are able to obtain financial information for 12,570 of the 14,623 WMS firms resulting in a panel of 141,620 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 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 five years prior to their survey date.

3. The specific WMS questions used to score the decentralisation of their decision processes are given in Appendix A, along with further general details of the dataset.

4. 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.

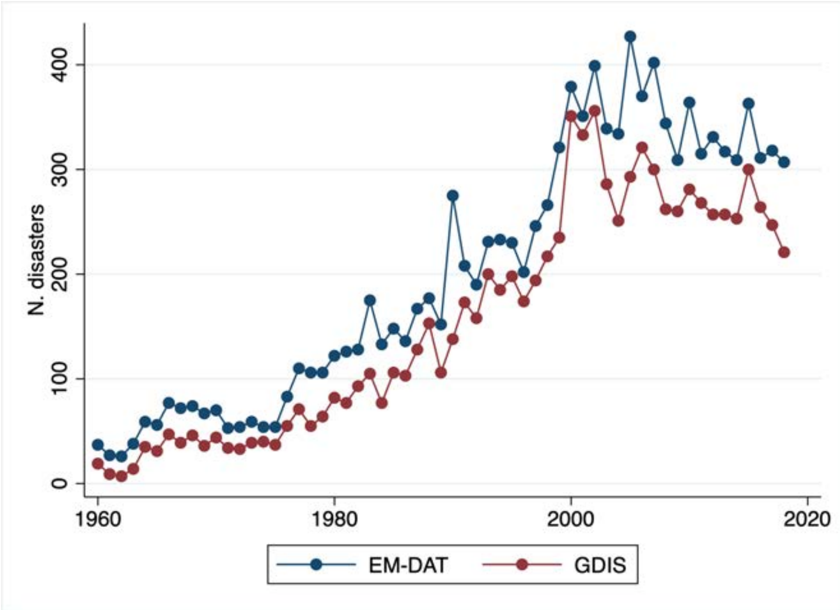
2.2 Natural Disasters and Disaster Exposure

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 redresses this by matching the location names in EM-DAT to standardised units taken from the Global Administrative Areas database (GADM 2018) and obtaining latitude and longitude coordinates of the unit centroids. GDIS only includes disasters that were able to be 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-total coverage and droughts the lowest coverage at around 64% of droughts recorded in EM-DAT appearing in GDIS. However, because the majority of disasters in EM-DAT are floods and storms, the two datasets track each other closely as shown in figure 1, which plots the number of disasters observed in both datasets over time.[5]

5. Figures B1 and B2 in the appendix 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.[6] 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 14,623 WMS firms we are able to accurately geolocate 10,020.[7] We then calculate the linear distance between firms' precise location and the location centroid for every natural disaster recorded in GDIS. Firms are classified as exposed to any particular event if this linear distance is less than or equal to 60km. 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 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 pertian 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

6. 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 attentuation bias caused by inaccuracy in their location. In Appendix B.4 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.

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

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/commune/village), the vast majority of the locations are administrative level 1 (typically state/province/region). 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. The fact that we observe significant impacts of disasters on firms despite the attenuation bias created by this measurement error reassures us that the measure, while inevitably imperfect, retains adequate signal to provide insight.

2.3 Sample Characteristics

Our analysis sample is restricted to firms in the WMS that were successfully geolocated and matched to the HO financial data.[8] Table 1 shows that firms in the analysis sample have slightly lower levels of decentralisation on average relative to the full WMS sample but they are statistically similar in terms of management practices. Relative to the full WMS, the average firm in our analysis sample has a larger workforce and European firms are over-represented making up 52% of the analysis sample in comparison to 40% of the WMS sample, predominantly due to higher coverage of European firms in the HO data. North American and African firms, by contrast, are underrepresented, which is again due to differential coverage of the HO data across countries. While there are also significant differences in other firm attributes, such as workforce skills, exporter status and family ownership the magnitude of the differences is small.

Table 1: Sample characteristics

	(1) Full WMS	(2) Analysis sample	Difference
Management	-0.02	-0.01	0.01 (0.23)
Decentralisation	-0.02	-0.03	-0.01 (0.01)
Employment	844	891	47 (0.07)
Workforce degree %	0.16	0.16	-0.01 (0.00)
Family firm %	0.40	0.41	0.01 (0.01)
Exporter %	0.49	0.52	0.03 (0.00)
MNE %	0.38	0.40	0.01 (0.02)
Africa %	0.05	0.01	-0.04 (0.00)
Asia %	0.16	0.15	-0.01 (0.00)
Europe %	0.40	0.52	0.12 (0.00)
Latin America %	0.23	0.21	-0.02 (0.00)
North America %	0.12	0.07	-0.05 (0.00)
Oceania %	0.04	0.04	0.00 (0.41)
N firms	14623	7858	

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.

8. Table A1 in Appendix A shows the country composition of our analysis sample.

3 The Impact of Natural Disasters on Firm Performance

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. Assuming the occurrence of natural disasters is exogenous to firm performance, the direct impact of disaster exposure on firms can be estimated via equations of the following form

$$\Delta y_{ijct+1} = \beta_0 D_{it} + \beta_1 M_i + \beta_2 X_{it} + \tau_t + \iota_j + \kappa_c + \epsilon_{it}, \tag{1}$$

where subscripts i, j, c and t denote firms, industries, countries and years respectively. Δy_{ijt+1} is the future growth (between $t+1$ and t) of a particular outcome such as inputs, outputs or is a dummy indicator for survival. D_{it} is a dummy that indicates whether firm i is exposed to a disaster in year t, with the definition of 'exposure' described in section 2. M are continuous measures of firms' management practices as described in Section 2, X is a vector of firm characteristics including firm age, the share of employees with a degree and size, measured as log employment for outcomes other than employment and log fixed assets otherwise. τ, ι and κ are vectors of time, 2-digit industry and country of location dummies respectively and ϵ an unobserved mean-zero disturbance.

Second, we examine whether management practices affect the impact of natural disasters using specifications of the following form

$$\Delta y_{ijct+1} = \beta_0 D_{it} + \beta_1 M_i + \beta_2 X_{it} + \beta_3 (D_{it} * M_i) + \beta_4 (D_{it} * X_{it}) + \tau_t + \iota_j + \kappa_c + \epsilon_{it}. \tag{2}$$

This is the same as equation (1) with the addition of interactions between the disaster dummy D and firm characteristics M and X. In this specification, we are primarily interested in the β_3 parameter, which indicate whether the impact of natural disasters is different for firms with relatively good management practices.[9]

Aside from survival, all outcomes we consider are *changes* in firm-level metrics such as capital, employment and value added. Any constant differences across firms in the *levels* of the outcomes are netted out.[10]

9. We include interactions between both management M and other firm attributes X to isolate the impact of management conditional on firm characteristics but also consider a variant on 2 that excludes this interaction. Comparing the β_3 coefficient across these specifications then highlights the extent to which any differential impact of disasters according to management practices operates via the impact of management on other firm attributes.

10. Specifically the Δy_{ijct+1} we consider are a dummy that equals 1 if year t is the last year firm i is observed and growth rate variables defined as

$$\frac{\ln(x_{it+s}) - \ln(x_{it})}{s}, \tag{3}$$

where x is one of capital, employment, value added. We consider $s \in [1, 2, 3]$ to examine whether impacts are short-lived or persist over several years and normalise by the lag considered s, to make growth rates comparable across time horizons. We also consider an alternative growth measure, inspired by Davis and Haltiwanger (1992)

$$\frac{1}{s}\left(\frac{x_{it+s} - x_{it}}{0.5\,(x_{it+s} + x_{it})}\right), \tag{4}$$

again normalising by the lag considered s, to make growth rates comparable across time horizons. As well as accommodating non-positive values of x outcomes, this measures incorporates extensive margin changes, taking the value of 2 and -2 for entrants and exitors respectively. The results using this alternative measure are qualitatively similar to those reported in the main text and we therefore relegate them to Appendix B for

Several points regarding equation (1) warrant comment. First, while the specification echos those of conventional event-studies, it only includes a single disaster indicator D rather than the conventional pre-/post- dummies or lags and leads. We adopt this approach as the definition of such variables is complicated when firms are exposed to disasters in multiple years, as observed - albeit relatively rarely - in our data. Second, is the issue of whether the β parameters on D and its interactions can be interpreted as the causal impact of disasters on firm performance. As stated above, the principal identification assumption we rely on is that the timing of disasters is exogenous to the firm performance metrics we consider. While this seems plausible, we are aware the validity of the assumption is challenged by our source of disaster data. Specifically, the threat to identification stems from the fact that disasters are included in the EM-DAT dataset if they meet one of several criteria, including numbers of deaths and people affected. It is possible that local characteristics, such as infrastructure quality may influence the extent to which people are affected by a particular natural disaster and also impact firm performance. In theory this could lead to omitted variable bias by systematically biasing the inclusion/exclusion of disasters used in the definition of D. In practice, however, we are unconcerned by this because of the multiplicity of criteria used to identify disasters in the EM-DAT data and our focus on growth rates in firm-level outcomes, which net out persistent differences across firms such as differences in infrastructure. Another threat to causal identification stems from selection of firms into areas. One may, for example, be concerned that firms of higher unobserved quality firms were less likely to locate in disaster-prone areas and had better management practices. Again, the first-differenced specification mitigates against this, as it effectively removes any persistent unobservable differences across firms.

Table 5 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). Different panels are restricted and full versions of equation (2), 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 columns) and survival (final column). Panel B has the same specification substituting disasters for management on the right hand side of the equation. This regressions validates the disaster variable: exposure to natural disasters reduces the growth in firms' capital, employment and value added as well as reducing the probability of firms' survival (although the latter effect is not statistically significant at the 10% level). The estimates of these effects are economically important when compared to the mean value of the outcome variables. The impacts on growth in capital, employment and value added growth amount to 17%, 60% and 25% reductions relative to the mean observed growth rates, while the impact on firm survival corresponds to roughly a 10% increase in the firm exit rate.[11] Panel C has management and disaster in the same regressions and includes additional linear controls. These point estimates remain essentially unchanged.

---

parsimony.

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

Table 2: Impact of disaster exposure and management on 1-year firm performance

	(1)	(2)	(3)	(4)
	Log differences $(t, t+1)$			
	Capital	Emp.	VA	Survival
Panel A: Linear Management				
Management	0.002**	0.002**	0.005***	0.017***
	(0.001)	(0.001)	(0.001)	(0.005)
Panel B: Linear Disaster Exposure				
Disaster in year	-0.004*	-0.003*	-0.007**	-0.016
	(0.002)	(0.001)	(0.003)	(0.011)
Panel C: Linear Firm Characteristics				
Disaster in year	-0.004*	-0.002	-0.007**	-0.019*
	(0.002)	(0.001)	(0.003)	(0.011)
Management	0.002	0.001	0.007***	0.005
	(0.001)	(0.001)	(0.001)	(0.005)
Panel D: Linear Firm Characteristics and Management-Disaster Interraction				
Disaster in year	-0.004*	-0.002	-0.007**	-0.019*
	(0.002)	(0.001)	(0.003)	(0.011)
Management	0.001	0.001	0.006***	0.003
	(0.001)	(0.001)	(0.001)	(0.005)
(Management)* (Disaster)	0.004**	0.003*	0.004	0.012
	(0.002)	(0.001)	(0.003)	(0.011)
Panel E: Linear Firm Characteristics and Full Disaster Interractions				
Disaster in year	-0.004*	-0.002	-0.007**	-0.024**
	(0.002)	(0.001)	(0.003)	(0.012)
Management	0.001	0.001	0.006***	0.003
	(0.001)	(0.001)	(0.001)	(0.005)
(Management)* (Disaster)	0.005**	0.003*	0.004	0.017
	(0.002)	(0.002)	(0.003)	(0.012)
Dep. var. mean	0.024	0.005	0.032	0.979
N obs.	73624	59106	34985	112785
N firms	5294	4651	2701	7858

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 3. Growth rates are trimmed at the top and bottom 2% level. Dependent variable in column 4 is a dummy indicating that year t is the last year a firm is observed. 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 5 is one of our key results, which includes the interaction between disasters and management from equation (2). Panel E additionally includes interactions between other firm characteristics and disaster exposure. Both panels show firms with higher management scores experience significantly lower declines in capital and employment growth following disaster exposure than other firms. The magnitude of the interaction coefficient is roughly equal to the linear disaster effect indicating that firms with management practices one standard-deviation above average experience no negative impacts of disaster exposure on growth.

Table B2 in Appendix B repeats the analysis of Table 2 using growth rates that account for extensive margin changes in the manner of Davis and Haltiwanger (1992). This shows accounting for firm exit increases the magnitude of the 'raw' disaster effects, and the finding that management mitigates the impact of natural disasters remains robust. Table B3 in Appendix B repeats the analysis of Table 2 looking over a three year horizon. The point estimates of the 'raw' disaster effects in Panel B remain negative but are only significant for employment growth and survival. The latter effect indicates that disasters don't merely expedite the failure of firms that were already likely to exit regardless of disaster exposure, but cause additional firms to exit who would not otherwise have done so.

4 Management Practices, Climate Risk Perceptions and Climate Change Adaption

The results of the previous section suggest structured management practices protect firms from the negative impacts of natural disasters. This section provides evidence on two channels that might explain this finding: managerial awareness of climate-related risks and firm-level adaptation. We exploit 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).[12]

Since we can only conduct this analysis on the most recent WMS wave, we consider different natural disaster exposure 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 60km of at least one disaster in a particular decade and zero otherwise. As well as examining the association between the climate scores and exposure to 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:

$$\begin{aligned} P_i = \beta_0 D_{i2010s} + \beta_1 M_i + \beta_2 X_i + \beta_3 (M_i * D_{i2010s}) + \beta_4 (X_i * D_{i2010s}) + \\ \beta_5 D_{i1970s} + \beta_6 (M_i * D_{i1970s}) + \beta_7 (X_i * D_{i1970s}) + \iota_j + \kappa_c + \epsilon_i \end{aligned} \quad (5)$$

where D now denotes a dummy for being located in disaster-exposed area in the subscripted decade and P is a firms' standardised risk perception score. We are specifically interested in the parameter β_3, as this denotes whether firms with high management scores in areas that have recently experienced a disaster are more likely to perceive climate change and disasters as a risk to their business. In other words, it indicates whether such firms are more perceptive of the

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

disaster risks they face.

Table 3 contains estimates of the the parameters of interest in equation (5). As well as the full specification shown in column (4), the initial columns of the table contain estimates from more restrictive specifications. Column (1) first excludes firm characteristics and the controls for disasters in the 1970s. This shows a positive association between whether firms perceive disasters as a risk to their business and whether they are located in an area that recently experienced a disaster.[13] Column (2) then adds firm characteristics linearly and finds that firms with higher management scores are more likely to consider climate change as a risk to their business. This suggests one advantage of superior management is greater awareness in general. This hides heterogeneity by location, which is revealed in column (3) when we include an interaction between disaster exposure and management (as well as other disaster interactions with firm observables). Well-managed firms are significantly more likely to perceive disasters in places that have actually experienced disasters, and the linear term on management is now small and insignificant. Hence, the positive association between management and perceived climate risk is solely due to firms located in an area that recently experienced a natural disaster. Finally, column (4) adds controls for disasters in the 1970s (and interactions between this control and firm characteristics), which strengthens both the impact of overall disaster exposure on firms' risk perceptions and interaction term with management practices.

Overall, Table 3 provides evidence that firms with better management processes in areas that are exposed to natural disasters 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. (2022), 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.[14] While awareness alone is unlikely to affect firm performance, it may lead firms to develop contingency plans that render them more able to respond effectively to disruption caused by disasters and may thereby be one factor why structured management practices mitigate the negative impacts of natural disasters on firm performance.

13. To judge the magnitude of this effect, recall that our measure of climate change risk perceptions is standardised to have standard deviation one. Hence, being in an area that recently experienced a natural disaster increases firms' climate change risk perceptions by a tenth of a standard deviation.

14. Table B5 in Appendix B repeats the most comprehensive specification in column (4) of Table 3 for the separate components of management practices. This shows the interaction between management and disaster exposure is equally strong for operations and monitoring management and is also moderately strong for the target management score. By contrast, there is no significant association between human resources management and climate risk perceptions, regardless of firm location.

Table 3: Perceptions of climate change risk and Management

	(1)	(2)	(3)	(4)
Any disaster 2010-2018	0.108*	0.119**	0.119*	0.154**
	(0.060)	(0.061)	(0.061)	(0.064)
Management		0.086***	0.031	0.025
		(0.030)	(0.043)	(0.043)
(Management) * (Disaster 2010-2018)			0.105*	0.150**
			(0.058)	(0.066)
Any disaster 1970-1979				-0.099
				(0.097)
(Management) * (Disaster 1970-1979)				-0.078
				(0.079)
N obs.	1320	1320	1320	1320
Linear Firm Characteristics	No	Yes	Yes	Yes
Firm Char.-Disaster Interactions	No	No	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	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.

We next examine the influences on climate adaptation by estimating variants of the following equation:

$$\begin{aligned} A_i = & \beta_0 D_{i2010s} + \beta_1 M_i + \beta_2 X_i + \beta_3 (M_i * D_{i2010s}) + \beta_4 (X_i * D_{i2010s}) + \\ & \beta_5 D_{i1970s} + \beta_6 (M_i * D_{i1970s}) + \beta_7 (X_i * D_{i1970s}) + \beta_8 P_i + \beta_9 (M_i * P_i) + \iota_j + \kappa_c + \epsilon_i \end{aligned} \tag{6}$$

where A is a firm's standardised climate adaptation score and all other notation is as before. In addition to firm attributes M and X, 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 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 4 contains estimates of the main parameters of interest from equation (6). Column (1) first shows firms in areas that experienced a disaster between 2010 and 2018 are more likely to have implemented measures to adapt to climate change, which column (2) shows is robust to controlling for firm characteristics. In addition, column (2) shows that firms with high management scores are significantly more likely to take actions to adapt to climate change. Subsequent columns show this association is robust to a range of additional controls. Column (4) shows the association between management and adaptation does not differ significantly according to the recent disaster exposure of firms' locations while column (5) adds measures of climate risk perception. This shows firms who perceive climate change to be a risk to their business are also more likely to have implemented measures to try and reduce the impact of such risks. Interestingly, the interaction term between management and risk perceptions is positive and significant, indicating that well-managed firms are relatively more likely to act on their perceptions of climate risk than other firms. Finally column (6) shows that all significant associations are robust to controlling for disaster exposure in the 1970s.[15]

Overall, the results in Table 4 indicate a substantial 'adaptation gap' between firms with highly structured management practices and other firms, suggesting the differential impact of natural disasters documented in 3 may become greater in the future if action is not taken to redress the relative lack of preparation by poorly managed firms.

Table 4: Association between climate change adaptation, management and disaster exposure

	(1)	(2)	(3)	(4)	(5)	(6)
Any disaster 2010-2018	0.127**	0.165***	-0.029	-0.031	-0.058	-0.059
	(0.055)	(0.054)	(0.058)	(0.058)	(0.057)	(0.063)
Management		0.187***	0.197***	0.150***	0.152***	0.155***
		(0.028)	(0.027)	(0.040)	(0.039)	(0.039)
(Management) * (Disaster 2010-2018)				0.087	0.041	0.024
				(0.054)	(0.054)	(0.062)
Risk perception					0.204***	0.206***
					(0.028)	(0.028)
(Management) * (Risk perception)					0.074***	0.074***
					(0.024)	(0.024)
N obs.	1320	1320	1320	1320	1320	1320
Linear Firm Characteristics	No	Yes	Yes	Yes	Yes	Yes
Firm Char.-Disaster Interactions	No	No	No	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country Dummies	No	No	Yes	Yes	Yes	Yes
1970s Disasters	No	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.

5 The Role of Decentralisation

Aghion et al. (2021), find that decentralised firms performed better during the Great Recession, which raises the question of whether decentralisation is driving the results above. Table 5 first examines whether decentralisation protects firms from the negative effects of natural disasters by implementing the same specifications as in Table 2 but replacing firms' management scores with their (similarly standardized) decentralisation scores.

Panels A and C of Table 5 show that decentralised firms are significantly more likely to grow in terms of jobs and value added and to survive. In panels D and E we include interactions

15. Table B6 in Appendix B re-estimates the most general specification of column (6) of Table 4 for the separate components of management practices. It shows that the associations between management and adaptation are broadly similar across all dimensions of management practices.

between decentralisation and disasters. In contrast with management, none of these interactions are significant in the first three columns, which pertain to growth in inputs and output, whereas the final column shows that decentralised firms are less likely to exit following a disaster. A firm with a one standard deviation higher decentralisation score than the average firm experienced no rise in exit following natural disaster exposure.[16]

Table 5: Impact of disaster exposure and decentralisation on one-year ahead firm performance

	(1)	(2)	(3)	(4)
	Log differences $(t, t+1)$			
	Capital	Emp.	VA	Survival
Panel A: Linear Decentralisation				
Decentralisation	-0.000	0.002***	0.003**	0.009*
	(0.001)	(0.001)	(0.001)	(0.005)
Panel B: Linear Disaster Exposure				
Disaster in year	-0.004*	-0.003*	-0.007**	-0.016
	(0.002)	(0.001)	(0.003)	(0.011)
Panel C: Linear Firm Characteristics				
Disaster in year	-0.004*	-0.002	-0.007**	-0.020*
	(0.002)	(0.001)	(0.003)	(0.011)
Decentralisation	-0.000	0.002**	0.003**	0.014***
	(0.001)	(0.001)	(0.001)	(0.005)
Panel D: Linear Firm Characteristics and Decentralisation-Disaster Interraction				
Disaster in year	-0.004*	-0.002	-0.007**	-0.019*
	(0.002)	(0.001)	(0.003)	(0.011)
Decentralisation	0.000	0.001*	0.002	0.009*
	(0.001)	(0.001)	(0.001)	(0.005)
(Decentralisation)* (Disaster)	-0.000	0.001	0.002	0.028**
	(0.002)	(0.001)	(0.003)	(0.012)
Panel E: Linear Firm Characteristics and Full Disaster Interractions				
Disaster in year	-0.004*	-0.002	-0.007**	-0.024**
	(0.002)	(0.001)	(0.003)	(0.012)
Decentralisation	0.000	0.001*	0.002	0.009*
	(0.001)	(0.001)	(0.001)	(0.005)
(Decentralisation)* (Disaster)	-0.000	0.001	0.002	0.030**
	(0.002)	(0.001)	(0.003)	(0.012)
Dep. var. mean	0.024	0.005	0.032	0.979
N obs.	73624	59106	34985	112785
N firms	5294	4651	2701	7858

Note: same as note to Table 2.

We next examine the association between decentralisation and perceptions of climate risk by repeating the analysis of Table 3 using firms' decentralisation scores. Column (2) of Table 6 shows that, unlike management, decentralised firms are not more likely to regard natural disasters and

16. Table B4 in Appendix B repeats Panel E of Table 5 considering both management and decentralisation simultaneously. This shows that the results are robust to controlling for both management and decentralisation and interactions of both with disaster exposure.

climate change as risks to their business regardless of location as the coefficient is insignificant and small. When we include an interaction between disasters and decentralisation in columns (3) and (4), we see it is actually negative and significant (as opposed to the management interaction which was positive and significant), while the linear decentralisation coefficient becomes positive and significat. One interpretation of these results are that, instead of having relatively accurate risk perceptions, decentralised firms are simply more cautious or pessimistic when it comes to anticipated impacts of climate change. While this may lead them to develop contingency plans or invest in measures to adapt to climate change, which is indeed what we see below, such efforts could potentially be inefficient for decentralised firms located in areas where climate change poses little material risk to their business.

Table 6: Perceptions of climate change risk and decentralisation

	(1)	(2)	(3)	(4)
Any disaster 2010-2018	0.108*	0.115*	0.113*	0.143**
	(0.060)	(0.061)	(0.061)	(0.065)
Decentralised		0.000	0.081**	0.081**
		(0.027)	(0.036)	(0.036)
(Decentralised) * (Disaster 2010-2018)			-0.174***	-0.156***
			(0.052)	(0.058)
Any disaster 1970-1979				-0.099
				(0.099)
(Decentralised) * (Disaster 1970-1979)				-0.051
				(0.085)
N obs.	1320	1320	1320	1320
Linear Firm Characteristics	No	Yes	Yes	Yes
Firm Char.-Disaster Interactions	No	No	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes

Note: same as note to Table 3.

Table 7 repeats the results of Table 4 but using decentralisation instead of management. As with climate risk perceptions, the association between climate adaptation and decentralisation is different to the association with management practices. While columns (2)-(4) show adaptation to climate change is more common among decentralised firms, this association disappears when controls for climate risk perceptions are added in columns (5) and (6). Together with Table 6, we see that decentralised firms are more likely to perceive climate change as a risk to their business regardless of their location and this greater perceived risk is associated with the adoption of measures to reduce the impact of climate change. Unlike management practices, however, the propensity of firms to act of their perceptions of risk is no stronger for decentralised firms than for other firms and there is no 'adaptation gap' indicating that decentralised firms are adapting more than centralised firms conditional on their risk perceptions.

Table 7: Association between climate change adaptation, decentralisation and disaster exposure

	(1)	(2)	(3)	(4)	(5)	(6)
Any disaster 2010-2018	0.127**	0.161***	-0.039	-0.042	-0.072	-0.080
	(0.055)	(0.055)	(0.060)	(0.060)	(0.059)	(0.063)
Decentralised		0.095***	0.057**	0.071*	0.052	0.053
		(0.027)	(0.027)	(0.038)	(0.037)	(0.038)
(Decentralised) * (Disaster 2010-2018)				-0.031	0.012	0.003
				(0.053)	(0.052)	(0.058)
Risk perception					0.213***	0.215***
					(0.028)	(0.028)
(Decentralised) * (Risk perception)					-0.040	-0.043
					(0.027)	(0.027)
N obs.	1320	1320	1320	1320	1320	1320
Linear Firm Characteristics	No	Yes	Yes	Yes	Yes	Yes
Firm Char.-Disaster Interactions	No	No	No	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country Dummies	No	No	Yes	Yes	Yes	Yes
1970s Disasters	No	No	No	No	No	Yes

Note: same as note to Table 4.

In short, the management results are not affected by decentralisation. While we see that, similar to well-managed firms, decentralised firms are less negatively impacted by natural disasters this is primarily through a higher survival probability. We find evidence that decentralised firms are investing more in adaption, but that this investment is not well targeted, as it is driven by perceptions of disaster risk, which are actually *lower* in the places where disasters are more frequent. This suggests that, while decentralised decision making may help firms survive negative shocks, a countervailing advantage of centralisation (and management) may be more accurate perceptions of risk.

6 Conclusions

This paper shows that natural disasters have a range of negative impacts on firm performance. Analysing data from 33 countries spanning 30 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 capital and employment growth following natural disaster exposure. Novel data on firms' environmental attitudes suggests the greater resilience of well-managed firms to natural disasters may be due to more accurate perceptions of the climate-related risks they face. We also find evidence for another possible mechanism; that they are more likely to act on their risk perceptions by implementing measures to try and reduce the impact of climate change on their business. Decentralised firms, like well managed firms, are also better at dealing with disasters and more likely to have implemented climate adaptation measures. However, they perceive climate change as a risk more strongly in places where natural disasters are not common, suggesting their climate change adaptation may be inefficient.

As natural disasters are likely to increase in coming years due to climate change, the relationship between management practices and resilience to disasters is likely to grow in importance with firms that are currently poorly-managed at risk of falling further behind. That well-managed firms are already more likely to be implementing measures to insulate themselves from the impacts climate change suggests policies aiming to bolster the climate resilience of firms may explicitly try to target those with relatively poor management practices. Indeed, the relationship between management practices and the impacts of disasters implies that helping these firms improve their management practices is itself a method that would reduce their exposure to negative impacts of climate change.

These findings raise several questions. First, the mechanisms underlying the links between firm management practices and disaster impacts warrant further examination. Second, it would be interesting to examine whether the relationships between disasters, management and firm outcomes are mediated by national institutions and policies. We were unable to pursue such heterogeneity analysis in this application due to sample size constraints. However, given the majority of research on the impact of natural disasters focuses on specific countries, more cross-country work such as that presented here would be valuable and could provide insight on such questions.

Given the range of positive impacts that management practices have been shown to have on a range of firm-level outcomes (Bloom et al. 2019), improving management practices should already be an aim of policy makers. In light of climate change and the results in this paper, it should become an imperative.

References

Acevedo, Sebastian, Mico Mrkaic, Natalija Novta, Evgenia Pugacheva, and Petia Topalova. 2020. "The Effects of Weather Shocks on Economic Activity: What are the Channels of Impact?" *Journal of Macroeconomics* 65 (September): 103207.

Adhvaryu, Achyuta, Namrata Kala, and Anant Nyshadham. 2020. "The Light and the Heat: Productivity Co-Benefits of Energy-Saving Technology." *The Review of Economics and Statistics* 102, no. 4 (October): 779–792.

———. 2022. "Management and Shocks to Worker Productivity." *Journal of Political Economy* 130, no. 1 (January 1, 2022): 1–47.

Aghion, Philippe, Nicholas Bloom, Brian Lucking, Raffaella Sadun, and John Van Reenen. 2021. "Turbulence, Firm Decentralization, and Growth in Bad Times." *American Economic Journal: Applied Economics* 13, no. 1 (January 1, 2021): 133–169.

Allcott, Hunt, Sendhil Mullainathan, and Dmitry Taubinsky. 2014. "Energy policy with externalities and internalities." *Journal of Public Economics* 112 (April): 72–88.

Auffhammer, Maximilian, and Tamma A. Carleton. 2018. "Regional Crop Diversity and Weather Shocks in India." *Asian Development Review* 35, no. 2 (August): 113–130.

Augier, Mie, and David J. Teece. 2009. "Dynamic Capabilities and the Role of Managers in Business Strategy and Economic Performance." *Organization Science* 20, no. 2 (April): 410–421.

Balboni, C, J Boehm, and M Waseem. 2023. "Firm Adaptation in Production Networks: Evidence from Extreme Weather Events in Pakistan." *Working Paper.*

Bandiera, Oriana, Andrea Prat, Stephen Hansen, and Raffaella Sadun. 2020. "CEO Behavior and Firm Performance." *Journal of Political Economy* 128, no. 4 (April): 1325–1369.

Barrot, Jean-Noël, and Julien Sauvagnat. 2016. "Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks *." *The Quarterly Journal of Economics* 131, no. 3 (August 1, 2016): 1543–1592.

Besley, Timothy, and Torsten Persson. 2009. "Repression or Civil War?" *American Economic Review* 99, no. 2 (April 1, 2009): 292–297.

Bianchi, Nicola, and Michela Giorcelli. 2022. "The Dynamics and Spillovers of Management Interventions: Evidence from the Training within Industry Program." *Journal of Political Economy* 130, no. 6 (June 1, 2022): 1630–1675.

Bloom, N., and J. Van Reenen. 2007. "Measuring and Explaining Management Practices Across Firms and Countries." *The Quarterly Journal of Economics* 122, no. 4 (November 1, 2007): 1351–1408.

Bloom, Nicholas, Erik Brynjolfsson, Lucia Foster, Ron Jarmin, Megha Patnaik, Itay Saporta-Eksten, and John Van Reenen. 2019. "What Drives Differences in Management Practices?" *American Economic Review* 109, no. 5 (May 1, 2019): 1648–1683.

Bloom, Nicholas, Christos Genakos, Ralf Martin, and Raffaella Sadun. 2010. "Modern Management: Good for the Environment or Just Hot Air?" *The Economic Journal* 120, no. 544 (May 1, 2010): 551–572.

Bloom, Nicholas, Taka Kawakubo, Charlotts Meng, Paul Mizen, Rebecca Riley, Senga Tatsura, and John Van Reenen. 2022. "Managing Expectations: How better managed firms make better macro and micro forecasts." *POID Working Paper* No.23.

Bloom, Nicholas, Aprajit Mahajan, David McKenzie, and John Roberts. 2020. "Do Management Interventions Last? Evidence from India." *American Economic Journal: Applied Economics* 12, no. 2 (April 1, 2020): 198–219.

Bruhn, Miriam, Dean Karlan, and Antoinette Schoar. 2018. "The Impact of Consulting Services on Small and Medium Enterprises: Evidence from a Randomized Trial in Mexico." *Journal of Political Economy* 126, no. 2 (April): 635–687.

Capelle, Damien, Divya Kirti, Nicola Pierri, and Germán Villegas Bauer. 2024. "Mitigating Climate Change at the Firm level: Mind the Laggards." *Working Paper.*

Carvalho, Vasco M, Makoto Nirei, Yukiko U Saito, and Alireza Tahbaz-Salehi. 2021. "Supply Chain Disruptions: Evidence from the Great East Japan Earthquake*." *The Quarterly Journal of Economics* 136, no. 2 (March 24, 2021): 1255–1321.

Cavallo, Eduardo, Sebastian Galiani, Ilan Noy, and Juan Pantano. 2013. "Catastrophic Natural Disasters and Economic Growth." *The Review of Economics and Statistics* 95, no. 5 (December 1, 2013): 1549–1561.

Clò, Stefano, Francesco David, and Samuele Segoni. 2024. "The impact of hydrogeological events on firms: Evidence from Italy." *Journal of Environmental Economics and Management* 124 (March): 102942.

Dar, Manzoor H., Alain de Janvry, Kyle Emerick, David Raitzer, and Elisabeth Sadoulet. 2013. "Flood-tolerant rice reduces yield variability and raises expected yield, differentially benefitting socially disadvantaged groups." *Scientific Reports* 3, no. 1 (November 22, 2013): 3315.

Davis, S. J., and J. Haltiwanger. 1992. "Gross Job Creation, Gross Job Destruction, and Employment Reallocation." *The Quarterly Journal of Economics* 107, no. 3 (August 1, 1992): 819–863.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken. 2012. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century." *American Economic Journal: Macroeconomics* 4, no. 3 (July 1, 2012): 66–95.

Elliott, Robert J.R., Eric Strobl, and Puyang Sun. 2015. "The local impact of typhoons on economic activity in China: A view from outer space." *Journal of Urban Economics* 88 (July): 50–66.

GADM. 2018. *Database of Global Administrative Areas.*

Giorcelli, Michela. 2019. "The Long-Term Effects of Management and Technology Transfers." *American Economic Review* 109, no. 1 (January 1, 2019): 121–152.

Haas, R de, R Martin, M Muuls, and M Schweiger. 2022. "Managerial and financial barriers during the green transition." *POID Working Paper* No.55.

Huber, Kilian, Volker Lindenthal, and Fabian Waldinger. 2021. "Discrimination, Managers, and Firm Performance: Evidence from "Aryanizations" in Nazi Germany." *Journal of Political Economy* 129, no. 9 (September 1, 2021): 2455–2503.

Hultgren, Andrew, Tamma Carleton, Michael Delgado, Diana R. Gergel, Michael Greenstone, Trevor Houser, Solomon Hsiang, Amir Jina, Robert E. Kopp, Steven B. Malevich, Kelly McCusker, Terin Mayer, Ishan Nath, James Rising, Ashwin Rode, and Jiacan Yuan. 2022. "Estimating Global Impacts to Agriculture from Climate Change Accounting for Adaptation." *SSRN Electronic Journal.*

Iacovone, Leonardo, William Maloney, and David McKenzie. 2022. "Improving Management with Individual and Group-Based Consulting: Results from a Randomized Experiment in Colombia." *The Review of Economic Studies* 89, no. 1 (January 10, 2022): 346–371.

IPCC. 2023. *Intergovernmental Panel On Climate Change Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.* 1st ed. Cambridge University Press, June 22, 2023.

Kahn, Matthew E. 2005. "The Death Toll from Natural Disasters: The Role of Income, Geography, and Institutions." *Review of Economics and Statistics* 87, no. 2 (May): 271–284.

Kocornik-Mina, Adriana, Thomas K. J. McDermott, Guy Michaels, and Ferdinand Rauch. 2020. "Flooded Cities." *American Economic Journal: Applied Economics* 12, no. 2 (April): 35–66.

Lamorgese, Andrea, Megha Patnaik, Andrea Linarello, and Fabiano Schivardi. 2024. "Management Practices and Resilience to Shocks: Evidence from COVID-19." *Management Science* (March 20, 2024): mnsc.2021.01341.

Lazear, Edward P., Kathryn L. Shaw, and Christopher T. Stanton. 2015. "The Value of Bosses." *Journal of Labor Economics* 33, no. 4 (October): 823–861.

Li, Wei, Paul Mizen, Rebecca Riley, and Jakob Schneebacher. 2023. "Managing to Adapt: Structured Management Practices and Firm Resilience." *Working Paper.*

Martin, Ralf, Mirabelle Muûls, Laure B. De Preux, and Ulrich J. Wagner. 2012. "Anatomy of a paradox: Management practices, organizational structure and energy efficiency." *Journal of Environmental Economics and Management* 63, no. 2 (March): 208–223.

Masuda, Yuta J., Teevrat Garg, Ike Anggraeni, Kristie Ebi, Jennifer Krenz, Edward T. Game, Nicholas H. Wolff, and June T. Spector. 2021. "Warming from tropical deforestation reduces worker productivity in rural communities." *Nature Communications* 12, no. 1 (March 11, 2021): 1601.

Michler, Jeffrey D., Kathy Baylis, Mary Arends-Kuenning, and Kizito Mazvimavi. 2019. "Conservation agriculture and climate resilience." *Journal of Environmental Economics and Management* 93 (January): 148–169.

Rosvold, E., and H. Buhaug. 2021. *Geocoded Disasters (GDIS) Dataset.*

Rosvold, Elisabeth L., and Halvard Buhaug. 2021. "GDIS, a global dataset of geocoded disaster locations." *Scientific Data* 8, no. 1 (February 16, 2021): 61.

Scur, Daniela, Raffaella Sadun, John Van Reenen, Renata Lemos, and Nicholas Bloom. 2021. "The World Management Survey at 18: lessons and the way forward." *Oxford Review of Economic Policy* 37, no. 2 (June 29, 2021): 231–258.

Shin, Jieun. 2023. "Fuel Prices and Carbon Emissions: The Role of Structured Management Practices." *Working Paper.*

Somanathan, E., Rohini Somanathan, Anant Sudarshan, and Meenu Tewari. 2021. "The Impact of Temperature on Productivity and Labor Supply: Evidence from Indian Manufacturing." *Journal of Political Economy* 129, no. 6 (June 1, 2021): 1797–1827.

Tanaka, Ayumu. 2015. "The impacts of natural disasters on plants' growth: Evidence from the Great Hanshin-Awaji (Kobe) earthquake." *Regional Science and Urban Economics* 50 (January 1, 2015): 31–41.

Teece, David J. 2007. "Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance." *Strategic Management Journal* 28, no. 13 (December): 1319–1350.

Zhang, Peng, Olivier Deschenes, Kyle Meng, and Junjie Zhang. 2018. "Temperature effects on productivity and factor reallocation: Evidence from a half million chinese manufacturing plants." *Journal of Environmental Economics and Management* 88 (March): 1–17.

A Supplementary Data Information

Management-Accounting Panel Dataset

As described above, the data used in our analysis features a panel element. This is built by combining the management survey waves with the accounting panel data, and then interpolating and back-filling characteristics from the WMS over missing years. For example, if we observe the skill composition of a firm's workforce in the 2004 WMS and again in the 2006 WMS, we linearly interpolate the data in the intervening years.

Firm-level Variables

Data on firms' sales, employment, capital, materials and payroll (the wage bill), is drawn from Historical Orbis accounting data. Value added is calculated as sales minus materials.[17] Other firm attributes are collected as part of the WMS, including information on plant and firm employment, the fraction of employees with a degree and organisational structure.

Management practices were scored following the methodology of Bloom and Van Reenen (2007), with practices grouped into four areas: *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.[18] 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. Our management measure averages the z-scores of all 18 dimensions and then z-scores this average again.

The decentralisation of firms' decision making processes is assessed along three dimensions using the following questions

1. What agreement would your plant need from central head quarters to hire a full-time permanent shop floor worker?

2. How much of sales and marketing is carried out at the plant level rather than at the central head quarters?

3. Where are decisions taken on new product introductions - at the plant, at the central head quarters or at both?

with higher scores given to firms whose responses indicate more decentralised decision processes in the sense that the plant has autonomy over decisions independent of the central head quarters.

17. 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. For observations which still had missing values for materials we assumed that the fraction of materials in sales was equal to the industry-year average.

18. Since the operations and monitoring concepts overlap we often group them together as "monitoring".

As with the management indicators, we combine the scores for these questions into a single measure of decentralisation by standardising the three scores, calculating their mean and then standardising the mean to have mean equal to zero and standard deviation equal to one.

Sample Coverage

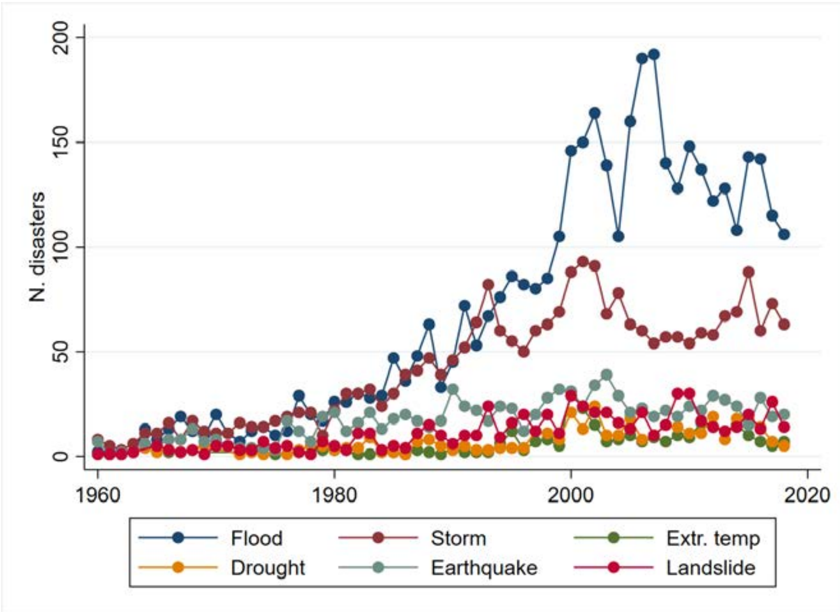
Table A1: Analysis sample by country

	(1) N Firms	(2) N Obs.
Argentina	216	1740
Australia	285	3155
Brazil	774	7615
Canada	235	1835
Chile	305	3162
China	431	5206
Colombia	167	838
Ethiopia	4	23
France	373	7673
Germany	363	5516
Ghana	26	138
Greece	458	7521
India	460	6549
Italy	519	10488
Japan	86	1379
Kenya	33	33
Mexico	217	1378
Mozambique	5	20
New Zealand	58	629
Nicaragua	5	20
Nigeria	11	170
Poland	215	4213
Portugal	245	4546
Republic of Ireland	74	1149
Singapore	276	3493
Spain	251	5222
Sweden	215	4178
Tanzania	25	163
Turkey	265	2441
United Kingdom	809	16682
United States	389	5153
Vietnam	48	405
Zambia	15	52
Total	7858	112785

B Supplementary Results

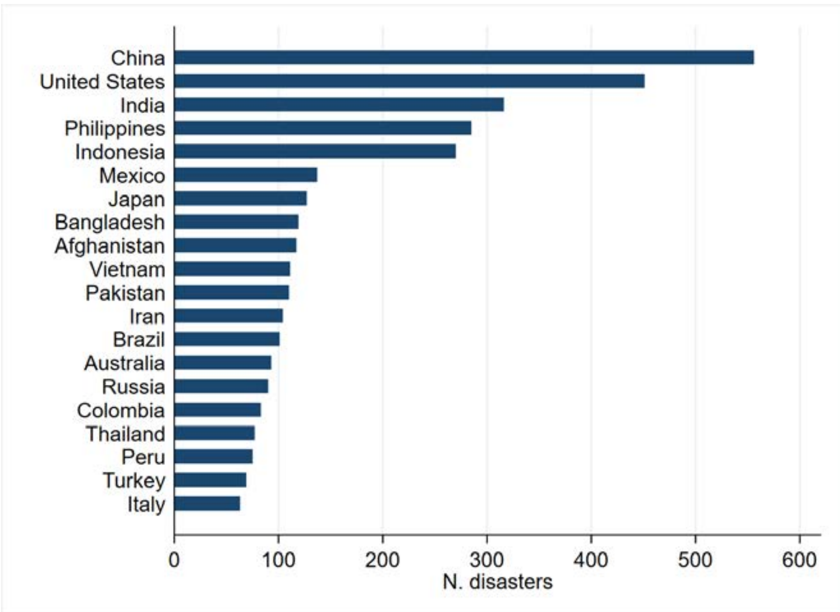
B.1 Natural disaster descriptives

Figure B1: Natural disasters recorded in GDIS, by type of disaster



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

Figure B2: 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.

B.2 Additional Disaster Impact Estimates

Table B2: Impact of disaster exposure on 1-year firm performance: DHS growth rates

	(1)	(2)	(3)	(4)
	DHS growth rates $(t, t+1)$			
	Capital	Emp.	VA	Survival
Panel A: Linear Management				
Management	0.007***	0.007***	0.010***	0.017***
	(0.002)	(0.002)	(0.002)	(0.005)
Panel B: Linear Disaster Exposure				
Disaster in year	-0.012***	-0.007**	-0.009**	-0.016
	(0.004)	(0.003)	(0.004)	(0.011)
Panel C: Linear Firm Characteristics				
Disaster in year	-0.012***	-0.008**	-0.009**	-0.019*
	(0.004)	(0.003)	(0.004)	(0.011)
Management	0.004**	0.003	0.009***	0.005
	(0.002)	(0.002)	(0.002)	(0.005)
Panel D: Linear Firm Characteristics and Management-Disaster Interraction				
Disaster in year	-0.012***	-0.008**	-0.009**	-0.019*
	(0.004)	(0.003)	(0.004)	(0.011)
Management	0.004**	0.002	0.009***	0.003
	(0.002)	(0.002)	(0.002)	(0.005)
(Management)* (Disaster)	0.001	0.001	0.002	0.012
	(0.003)	(0.003)	(0.004)	(0.011)
Panel E: Linear Firm Characteristics and Full Disaster Interractions				
Disaster in year	-0.012***	-0.007**	-0.009**	-0.024**
	(0.004)	(0.003)	(0.004)	(0.012)
Management	0.003*	0.002	0.008***	0.003
	(0.002)	(0.002)	(0.002)	(0.005)
(Management)* (Disaster)	0.002	0.003	0.003	0.017
	(0.004)	(0.003)	(0.004)	(0.012)
Dep. var. mean	-0.011	-0.042	0.014	0.979
N obs.	75191	60796	35542	112785
N firms	5550	5245	2737	7858

Note: same as note to Table 2 except that the dependent variable in columns 2-4 are one-year growth rates of the outcome in the column title defined according to equation 4.

Table B3: Impact of disaster exposure on 3-year firm performance

	(1)	(2)	(3)	(4)
	Log differences $(t, t+3)$			
	Capital	Emp.	VA	Survival
Panel A: Linear Management				
Management	0.002*	0.001	0.003***	0.083***
	(0.001)	(0.001)	(0.001)	(0.012)
Panel B: Linear Disaster Exposure				
Disaster in year	-0.002	-0.003***	-0.001	-0.055**
	(0.002)	(0.001)	(0.002)	(0.023)
Panel C: Linear Firm Characteristics				
Disaster in year	-0.002	-0.003***	-0.001	-0.055**
	(0.002)	(0.001)	(0.002)	(0.023)
Management	0.002**	0.001	0.006***	0.036***
	(0.001)	(0.001)	(0.001)	(0.013)
Panel D: Linear Firm Characteristics and Management-Disaster Interraction				
Disaster in year	-0.002	-0.003**	-0.001	-0.055**
	(0.002)	(0.001)	(0.002)	(0.023)
Management	0.002*	0.001	0.005***	0.036***
	(0.001)	(0.001)	(0.001)	(0.013)
(Management)* (Disaster)	0.001	0.001	0.001	0.001
	(0.002)	(0.001)	(0.002)	(0.022)
Panel E: Linear Firm Characteristics and Full Disaster Interractions				
Disaster in year	-0.002	-0.003**	-0.000	-0.065***
	(0.002)	(0.001)	(0.002)	(0.024)
Management	0.002*	0.001	0.005***	0.035***
	(0.001)	(0.001)	(0.001)	(0.013)
(Management)* (Disaster)	0.002	0.001	0.002	0.008
	(0.002)	(0.001)	(0.002)	(0.024)
Dep. var. mean	0.024	0.003	0.030	0.897
N obs.	66585	53018	31692	112785
N firms	5055	4298	2516	7858

Note: same as to Table 2, except that the dependent variables in columns 1-3 are three-year growth rates of the outcome in the column title and the dependent variable in column 4 is a dummy indicating that the last year a firm is observed lies within $[t, t+3]$.

Table B4: Impact of disaster exposure on 1-year firm performance: heterogeneity by management and decentralisation

	(1)	(2)	(3)	(4)
	Log differences $(t, t+1\ )$			
	Capital	Emp.	VA	Survival
Linear Firm Characteristics and Full Disaster Interractions				
Disaster in year	-0.004*	-0.002	-0.007**	-0.022*
	(0.002)	(0.001)	(0.003)	(0.012)
Management	0.001	0.001	0.006***	0.002
	(0.001)	(0.001)	(0.001)	(0.005)
Decentralisation	-0.000	0.001*	0.002	0.009*
	(0.001)	(0.001)	(0.001)	(0.005)
(Management)* (Disaster)	0.005**	0.003*	0.004	0.015
	(0.002)	(0.002)	(0.003)	(0.012)
(Decentralisation)* (Disaster)	-0.001	0.000	0.002	0.029**
	(0.002)	(0.001)	(0.003)	(0.012)
Dep. var. mean	0.024	0.005	0.032	0.979
N obs.	73624	59106	34985	112785
N firms	5294	4651	2701	7858

Note: same as to Table 2.

B.3 Climate Risk Perceptions and Climate Adaptation

Table B5: Climate risk perceptions and management components

	(1)	(2)	(3)	(4)
	Operations	Monitoring	Targets	People
Any disaster 2010-2018	0.138**	0.151**	0.155**	0.146**
	(0.064)	(0.065)	(0.064)	(0.064)
Mgmt. Component	0.021	-0.045	0.044	0.060
	(0.040)	(0.039)	(0.041)	(0.043)
(Mgmt. Component) * (Disaster 2010-2018)	0.158**	0.163***	0.112*	0.058
	(0.063)	(0.062)	(0.068)	(0.064)
Any disaster 1970-1979	-0.081	-0.098	-0.099	-0.077
	(0.097)	(0.097)	(0.098)	(0.097)
(Mgmt. Component) * (Disaster 1970-1979)	-0.074	-0.087	-0.066	-0.026
	(0.084)	(0.082)	(0.084)	(0.076)
N obs.	1320	1320	1320	1320
Linear Firm Characteristics	Yes	Yes	Yes	Yes
Firm Char.-Disaster Interactions	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes
Country Dummies	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.

Table B6: Association between climate change adaptation, management components and disaster exposure

	(1) Operations	(2) Monitoring	(3) Targets	(4) People
Any disaster 2010-2018	-0.074	-0.059	-0.066	-0.059
	(0.062)	(0.063)	(0.063)	(0.062)
Mgmt. Component	0.114***	0.115***	0.138***	0.117***
	(0.037)	(0.037)	(0.037)	(0.040)
(Mgmt. Component) * (Disaster 2010-2018)	-0.045	0.039	-0.018	0.057
	(0.062)	(0.057)	(0.059)	(0.061)
Risk perception	0.213***	0.213***	0.209***	0.206***
	(0.028)	(0.028)	(0.028)	(0.028)
(Mgmt. Component) * (Risk perception)	0.094***	0.061***	0.046**	0.065***
	(0.026)	(0.024)	(0.023)	(0.025)
N obs.	1320	1320	1320	1320
Linear Firm Characteristics	Yes	Yes	Yes	Yes
Firm Char.-Disaster Interactions	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes

Note: same as note to Table 4 except that 'Mgmt. Component' pertains to the specific management component denoted in the column title.

B.4 Main Results Estimated on Accurate Location Subsample

Table B7: Impact of disaster exposure and management 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	0.002**	0.002**	0.005***	0.017***
	(0.001)	(0.001)	(0.001)	(0.005)
Panel B: Linear Disaster Exposure				
Disaster in year	-0.004	-0.003**	-0.008***	-0.014
	(0.002)	(0.001)	(0.003)	(0.012)
Panel C: Linear Firm Characteristics				
Disaster in year	-0.003	-0.003*	-0.007**	-0.018
	(0.002)	(0.001)	(0.003)	(0.012)
Management	0.001	0.001	0.007***	0.004
	(0.001)	(0.001)	(0.001)	(0.005)
Panel D: Linear Firm Characteristics and Management-Disaster Interraction				
Disaster in year	-0.003	-0.003*	-0.007**	-0.018
	(0.002)	(0.001)	(0.003)	(0.012)
Management	0.001	0.001	0.006***	0.002
	(0.001)	(0.001)	(0.001)	(0.005)
(Management)* (Disaster)	0.004*	0.003**	0.003	0.011
	(0.002)	(0.001)	(0.003)	(0.012)
Panel E: Linear Firm Characteristics and Full Disaster Interractions				
Disaster in year	-0.003	-0.003*	-0.007**	-0.023*
	(0.002)	(0.001)	(0.003)	(0.012)
Management	0.001	0.001	0.006***	0.001
	(0.001)	(0.001)	(0.001)	(0.005)
(Management)* (Disaster)	0.005**	0.003*	0.002	0.016
	(0.002)	(0.002)	(0.003)	(0.012)
Dep. var. mean	0.023	0.004	0.030	0.979
N obs.	70068	56009	32156	108795
N firms	5074	4445	2521	7630

Note: same as note to Table 2 except that sample is restricted to firms who were either surveyed by the WMS prior to 2016 or were surveyed later and are single-site.

Table B8: Management and perceptions of climate change risk: single-site sample

	(1)	(2)	(3)	(4)
Any disaster 2010-2018	0.223**	0.240***	0.232**	0.320***
	(0.091)	(0.092)	(0.092)	(0.099)
Management		0.080	0.018	0.017
		(0.050)	(0.072)	(0.072)
(Management) * (Disaster 2010-2018)			0.111	0.165
			(0.096)	(0.106)
Any disaster 1970-1979				-0.319**
				(0.161)
(Management) * (Disaster 1970-1979)				-0.039
				(0.140)
N obs.	620	620	620	620
Linear Firm Characteristics	No	Yes	Yes	Yes
Firm Char.-Disaster Interactions	No	No	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes

Note: same as note to Table 3 except that sample is restricted to single-site firms.

Table B9: Disaster exposure, management and climate adaptation: single-site sample

	(1)	(2)	(3)	(4)	(5)	(6)
Any disaster 2010-2018	0.278***	0.300***	0.146*	0.143*	0.091	0.061
	(0.079)	(0.079)	(0.083)	(0.083)	(0.082)	(0.093)
Management		0.171***	0.171***	0.113**	0.124**	0.133**
		(0.041)	(0.042)	(0.057)	(0.055)	(0.055)
(Management) * (Disaster 2010-2018)				0.099	0.053	0.022
				(0.082)	(0.082)	(0.089)
Risk perception					0.183***	0.175***
					(0.037)	(0.038)
(Management) * (Risk perception)					0.078**	0.082**
					(0.034)	(0.034)
N obs.	620	620	620	620	620	620
Linear Firm Characteristics	No	Yes	Yes	Yes	Yes	Yes
Firm Char.-Disaster Interactions	No	No	No	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country Dummies	No	No	Yes	Yes	Yes	Yes
1970s Disasters	No	No	No	No	No	Yes

Note: same as note to Table 4 except that sample is restricted to single-site firms.