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Cost management in the era of natural disasters

LORENZO DAL MASO[a], SVEN HARTLIEB[b*], SARA LONGO[c] and FRANCESCO MAZZI[d]

[a]Department of Management, University of Bologna, Bologna, Italy; [b]Chair of Financial Accounting, Martin Luther University Halle-Wittenberg, Halle (Saale), Germany; [c]Department of Economics and Management, University of Padova, Padova, Italy; [d]Department of Economics and Management, University of Florence, Firenze, Italy

Using a sample of U.S. companies from 1993 to 2019, we examine how managers respond to natural disasters in their cost management decisions. We find no significant cost management response among firms located in directly affected regions, potentially due to offsetting forces. However, we find robust evidence that cost behaviour changes for firms located in geographically proximate but unaffected regions. Specifically, managers of these firms are more likely to reduce SG&A costs in response to sales declines following a nearby natural disaster. Additional analyses suggest that this response can be ascribed to irrational managerial pessimism, which is not economically justified, as neighbouring counties are not more likely to experience future natural disasters and these firms do not face contemporaneous sales declines after nearby events. These findings are consistent with salience theory, which suggests that managers become more pessimistic after being exposed to salient negative events, even when their firms are not directly affected. Overall, our results highlight the important role of behavioural biases in corporate cost management and are particularly timely given the increasing frequency and severity of natural disasters associated with climate change.

Keywords: cost stickiness; cost behaviour; natural disasters; climate change; salience bias
JEL CLASSIFICATIONS: M41; Q54

1. Introduction

Natural disasters regularly occur in the United States, causing extensive economic losses. As a prominent example, the monetary damage caused by Hurricane Katrina in 2005 amounted to approximately 125 billion USD, or 1% of the overall US GDP for that year (Felbermayr and Gröschl 2014). With climate science predicting that natural disasters are likely to become

*Corresponding author. Email: sven.hartlieb@wiwi.uni-halle.de
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more frequent in the future because of climate change and global warming (e.g. O'Brien et al. 2006, IPCC 2012), interest in climate-related risk, its consequences, and corporate responses to the occurrence of natural disasters has significantly increased in research and practice over recent years (e.g. Dal Maso et al. 2024). This study investigates the critical question of how managers – both from firms in directly affected areas and those in geographically proximate regions – adjust their cost management decisions in response to natural disasters.

Previous studies have documented that natural disasters create uncertainty and disrupt firms' operations (Dell et al. 2014, Cachon et al. 2019). Accordingly, firms in directly affected regions tend to exhibit weaker performance and face more restricted access to capital (e.g. Ginglinger and Moreau 2023, Pankratz et al. 2023). This also influences managerial behaviour, leading managers to act more cautiously by holding higher cash reserves (Huang et al. 2018).

Interestingly, natural disasters may also influence the risk perception of managers in neighbouring firms (i.e. firms located in geographically proximate but unaffected regions). A growing body of research examines how the proximity to disaster events affects managerial behaviour (Dessaint and Matray 2017, Kong et al. 2021, Huang et al. 2022). For instance, Dessaint and Matray (2017) argue that managers of firms located close to a hurricane-stricken area respond by temporarily holding more cash. They ascribe this phenomenon to salience bias, which is the tendency to overweight probabilities based on the ease with which events can be recalled (i.e. overweighting more readily available information). In the presence of such bias, subjects overestimate risks based on vividness, proximity, or emotional impact (Tversky and Kahneman 1973, Bordalo et al. 2012).

Against this background, we posit that natural disasters may influence corporate cost management decisions. The traditional view of cost behaviour has long postulated that variable costs change mechanically and proportionally with firm activity (Noreen 1991). However, empirical literature has shown that costs respond asymmetrically to changes in firm activity (e.g. Noreen and Soderstrom 1997, Anderson et al. 2003), a phenomenon commonly referred to as 'cost stickiness'. Importantly, this behaviour does not arise mechanically but is attributed to deliberate managerial decisions (Banker et al. 2018).

For firms in directly affected regions, direct operational consequences are expected. They are likely to experience asset damages, staff shortages and supply chain disruptions (e.g. Dell et al. 2014), leading to operational disturbances and slack resources. On the one hand, these disruptions may reduce cost stickiness. Managers may be forced to shut down or scale back operations when sales decline and may be unable to expand resources when sales increase because of operational constraints. On the other hand, these disruptions may increase cost stickiness. For instance, firms may face higher input costs when forced to rely on more expensive suppliers, or may retain resources due to adjustment frictions and uncertainty about the duration of the disruption. Institutional factors, such as insurance coverage and government aid, may further shape these cost adjustment decisions by mitigating financial constraints or facilitating recovery. These opposing forces make the cost management responses of firms in directly affected regions difficult to predict.

The focus of our study is therefore on the cost management responses of neighbouring firms, as theoretical arguments suggest that nearby natural disasters may also affect their cost management decisions. First, according to salience theory, managers of neighbouring firms may become more concerned about disaster risk after observing a nearby event and may therefore prefer to maintain smaller and more flexible operations. As a result, they may be more likely to reduce resources in response to sales decreases and less likely to expand resources during sales increases. Second, managers may rationally update their expectations about climate risk following a nearby disaster, leading to similar adjustments in cost management decisions. Third, even firms outside affected regions may experience indirect operational disruptions, for example when suppliers or employees in neighbouring areas are affected. Overall, these mechanisms suggest that managers of firms located near disaster areas may adopt more cautious and flexible cost management strategies, which constitutes our main hypothesis.

To test our hypothesis, we employ a set of 7,981 publicly listed US firms covering the period 1993–2019. Natural disasters are measured using county-level data from the Federal Emergency Management Agency (FEMA). Counties are identified as disaster areas when at least one natural disaster has occurred in the previous 12 months. Neighbouring counties are identified by matching each affected county with the 10 closest unaffected counties based on geographical distance.

By adopting the established asymmetric cost behaviour model proposed by Anderson et al. (2003), our results show that neighbouring firms exhibit lower cost stickiness on average, but only for more discretionary and future-oriented selling, general and administrative costs, and not for cost of goods sold. This suggests that managers in these firms are more cautious when adjusting discretionary expenses, probably as a result of the salience effect. Firms in directly affected regions in contrast do not exhibit significant changes in cost behaviour, arguably due to offsetting forces such as operational disruptions, insurance payouts or government assistance.

We conduct several additional tests to deepen our understanding of the main findings. These tests support the notion that the reaction of neighbouring firms to natural disasters can be ascribed to an irrational behavioural salience bias. Specifically, our results indicate that not only managers of firms in directly affected regions, but also those in neighbouring areas, systematically underestimate subsequent sales after a natural disaster. However, this reaction is not economically justified, as further results show that neighbouring counties are not more likely to experience future natural disasters, and that firms do not face contemporaneous sales declines following nearby disasters. Further tests provide insights into the role of disaster characteristics, such as frequency, severity, and the typicality of disaster exposure.

Our study contributes to the growing literature on the effects of natural disasters and climate-related risks. Previous research has documented the impact of natural disasters on capital markets (Dessaint and Matray 2017), the banking sector (Cortés and Strahan 2017), household wealth allocation (Shi et al. 2015), and analysts' behaviour (Kong et al. 2021). By examining cost decisions as fundamental corporate operating choices, our study offers novel insights into how managers respond to the actual and potential threats posed by natural disasters. In particular, we show that the cost management decisions of firms are also influenced by nearby disaster events. Given that climate change and its consequences are central to current public discourse – and are expected to intensify – these findings are relevant for a broad set of stakeholders concerned with corporate resilience and sustainability.

The remainder of this study is organised as follows. Section 2 describes relevant theories and develops the hypothesis. Section 3 presents the data and methodology. Section 4 reports descriptive statistics and discusses the main findings and the underlying mechanisms. Section 5 presents the results of further tests. Section 6 concludes the study by discussing findings, limitations, and future research opportunities.

2. Theory, prior evidence, and hypothesis development

2.1. *Cost management theory*

Cost behaviour theory distinguishes between fixed and variable costs based on how they respond to changes in firm activity. According to the traditional view, fixed costs are independent of current activity, whereas variable costs are assumed to change proportionally with activity levels (Noreen 1991). Hence, changes in sales are expected to translate proportionally into changes in variable costs, implying a largely mechanical relationship between cost and demand in which managerial discretion plays a limited role (Banker et al. 2018).

However, empirical research shows that costs do not adjust symmetrically to changes in activity. Instead, costs tend to increase more when activity rises than they decrease with decreasing activity, a phenomenon referred to as 'cost stickiness' (e.g. Anderson et al. 2003, Balakrishnan et al. 2004). In some cases, the opposite pattern ('anti-stickiness') can also be observed (e.g. Weiss 2010). This evidence suggests that cost behaviour cannot be fully explained by mechanical cost relationships but reflects deliberate managerial decisions that are 'subject to various constraints, incentives, and psychological biases' (Banker et al. 2018, p. 187).

A key driver of such decisions is the presence of resource adjustment costs. Adjusting resources, such as hiring or laying off employees, entails costs, which can make managers reluctant to reduce capacity when activity declines (e.g. Anderson et al. 2003, Balakrishnan and Gruca 2008, Banker and Byzalov 2014, Guenther et al. 2014). Managerial expectations about future demand constitute another central determinant (e.g. Anderson et al. 2003, Chen et al. 2019). When activity increases and managers expect this increase to persist, they are more likely to expand resources. Conversely, when activity declines, managers must decide whether to reduce or retain slack resources. If they anticipate a recovery, they are less likely to cut unused capacity in order to avoid current and future adjustment costs. Uncertainty may influence these decisions by affecting managerial expectations about future activity (e.g. Banker et al. 2014, Lee et al. 2020, Jin and Wu 2021). Moreover, agency-related motives, along with the role of governance mechanisms, have been shown to affect cost behaviour (e.g. Calleja et al. 2006, Chen et al. 2012, Chung et al. 2019).

Overall, prior literature suggests that cost behaviour reflects managerial discretion, particularly in the presence of adjustment costs and forward-looking expectations. These mechanisms are central to understanding how managers respond to external shocks, such as natural disasters, in their cost management decisions.

2.2. *Economic effects of natural disasters*

Increased exposure to natural disasters is a tangible consequence of climate change. While heat waves represent one prominent manifestation, climate science predicts that extreme weather events – such as cold spells, storms, floods, and hurricanes – will generally become more frequent and severe (e.g. O'Brien et al. 2006).

A growing body of evidence highlights the substantial economic consequences of such events. For instance, climate-related disasters are associated with increasing damage as global temperatures rise (Thomas et al. 2014), and are projected to impose significant macroeconomic costs in the future (Burke et al. 2015, BlackRock 2019). Individual events can have both immediate and persistent effects on economic activity. Hsiang and Jina (2014) show that severe cyclones have long-lasting negative effects on income per capita, comparable to major financial crises, while Cavallo et al. (2013) document an immediate downturn in economic activity, including consumption, following severe events.

Overall, prior research suggests that climate change and the associated increase in natural disasters can substantially disrupt economic activity at both the macroeconomic and local levels.

2.3. *Natural disasters and cost management*

2.3.1. *Firms in directly affected regions*

Prior research shows that natural disasters can weaken firms' financial and operating conditions (Hsu et al. 2018, Huang et al. 2018, Pankratz et al. 2023). This evidence is consistent with the substantial operational disruptions faced by firms in directly affected regions, including asset damage, labour shortages, and supply chain interruptions (Dell et al. 2014, Cachon et al. 2019). Such disruptions, in turn, can influence cost management decisions in opposing ways.

On the one hand, natural disasters may reduce cost stickiness because firms are forced to scale down operations due to these disruptions. In such situations, managers may need to cut resources more aggressively than implied by sales changes alone, as operational constraints limit their ability to maintain unused capacity.

On the other hand, natural disasters may increase cost stickiness. For example, firms may face higher labour costs due to overtime or the need to attract temporary workers, and disruptions to supply chains may require sourcing from more expensive or less reliable suppliers. In addition, adjustment frictions and uncertainty about the duration of the disruption may lead managers to retain resources in anticipation of a recovery. This reasoning is in line with prior research showing that firms exposed to climate-related risks face persistent operating and financial frictions, which can complicate timely resource adjustments (Ginglinger and Moreau 2023, Dal Maso et al. 2024).

These opposing effects may be further shaped by institutional factors, such as insurance coverage and government aid, which can mitigate financial constraints and facilitate post-disaster adjustments (e.g. Attary et al. 2020). Given the competing mechanisms outlined above, the overall effect for firms in directly affected regions is theoretically ambiguous. Accordingly, we do not formulate a directional hypothesis for these firms. Instead, we focus our hypothesis development on neighbouring firms, which are discussed in the following section.

2.3.2. *Firms in neighbouring (unaffected) regions*

A growing stream of literature shows that neighbouring firms may also adjust their behaviour in response to nearby events. For instance, Kong et al. (2021) show that analysts revise earnings forecasts downward for neighbouring firms. Dessaint and Matray (2017) document that managers increase cash holdings following nearby disasters, and Huang et al. (2022) find that banks restrict access to capital for firms located close to disaster areas.

These studies suggest that the effects of natural disasters extend beyond directly affected areas and shape managerial expectations and decision-making in neighbouring firms. Several mechanisms may explain why managers of these firms also adjust their cost management decisions.

First, cost management reactions to nearby disasters may be driven by behavioural biases. Individuals often rely on heuristics when making decisions, which can result in systematic distortions such as excessive pessimism (Tversky and Kahneman 1973). In particular, salience theory suggests that decision-makers overweight vivid or recently observed events and may overestimate the probability of negative outcomes (e.g. Bordalo et al. 2012).[1] As a result, managers may become more risk-averse and adjust their expectations about risk exposure and future demand. The vividness, proximity, and emotional impact of such events can lead managers to overestimate the risk to their own firm, even if the objective likelihood of a similar event has not changed (Tversky and Kahneman 1973, Bordalo et al. 2012). In addition, heightened uncertainty and anxiety may further reinforce risk-averse behaviour (Loewenstein et al. 2001).

Second, managers of neighbouring firms may adjust their decisions due to rational expectation updating. The occurrence of a nearby disaster may lead managers to reassess climate risks. In this case, adjustments in cost management reflect rational updates in expectations rather than behavioural biases.

Third, these reactions may be driven by indirect operational effects. Even if firms are not directly affected, they may experience disruptions through supply chains, labour markets, or customer relationships. For example, supply chain disruptions may arise when key transportation

[1]A vivid example by Tversky and Kahneman (1974, p. 1127) is as follows: ‘It is a common experience that the subjective probability of traffic accidents rises temporarily when one sees a car overturned by the side of the road.’

routes are impaired or suppliers are affected.[2] Similarly, staff shortages may occur when employees are located in impacted neighbouring regions. As a result, managers of firms in unaffected areas may still face operational constraints, which can lead them to adjust their cost structures.

The arguments discussed so far primarily point toward lower cost stickiness for neighbouring firms, as managers become more cautious and seek to maintain flexible operations. However, there is also a countervailing argument suggesting higher cost stickiness. Neighbouring firms may benefit from increased demand if competitors in affected areas are forced to scale back or cease operations. In such cases, managers may revise their demand expectations upward and become more optimistic about future activity. As a result, they may be more inclined to retain unused resources when sales decline or to expand resources more aggressively when sales increase, in order to capture additional market share.

Overall, we expect the first set of mechanisms to dominate because of both their number and theoretical strength, leading to lower cost stickiness in neighbouring firms following a natural disaster, as formulated in our main hypothesis below. Natural disasters increase perceived downside risk, which leads managers to adopt more cautious and conservative resource adjustment behaviour. These responses are likely to be immediate and persistent, as they are driven by both behavioural factors (e.g. salience and risk aversion) and rational expectation updating. Consistent with this view, Bourveau and Law (2021) show that experiencing a natural disaster has lifelong effects on analysts' risk assessments. This precautionary response is further reinforced by elevated uncertainty and limited visibility regarding the persistence and geographic spread of the shock. In contrast, potential demand gains arising from competitors' disruptions are inherently uncertain and difficult to sustain. They depend on temporary market imbalances and the speed with which affected competitors recover, which makes them both unpredictable and short-lived.

> Hypothesis**:** After the occurrence of a natural disaster in a neighbouring area, managers are more likely to decrease costs in response to a current sales decline and less likely to increase costs during sales growth.

3. Data and methods

3.1. *Sample selection*

For our empirical analyses, we rely on data from multiple databases. We use data on natural disasters from FEMA and accounting data from Compustat. Table 1 presents information on the sample selection, which follows prior literature (Kama and Weiss 2013, Banker and Byzalov 2014). Our sample includes all firms operating in the US, with data available on Compustat North America between 1993 and 2019. We use ZIP Codes to assign the corresponding Federal Information Processing Standard Publication (FIPS) county codes (available from the

[2]See, for example, the following excerpt from Sherwin-Williams' 2021 Form 10-K (p. 9):

> 'During 2021, Winter Storm Uri and Hurricane Ida caused significant damage to certain of our suppliers' facilities in Texas and Louisiana, respectively. These natural disasters and their impacts to certain of our suppliers resulted in unprecedented industry-wide supply chain disruptions, increased raw material and other costs, and significantly hindered our ability to manufacture the products needed to fully meet customer demand.'

It is important to note, however, that this example refers to two prominent natural disasters that did not occur in the direct 'neighbourhood' of Sherwin-Williams. Nevertheless, it provides a vivid illustration of how firms that are not directly affected by a disaster can still experience substantial operational constraints through supply-chain linkages.

US Department of Housing and Urban Development's Office of Policy Development and Research) to the firm headquarters. We follow prior literature (e.g. Loughran and Schultz 2005, Pirinsky and Wang 2006, Chaney et al. 2012) and proxy for a firm's location using its headquarters. We omit observations with missing state or ZIP Code information on the headquarters' location, total assets and employee data. Next, we remove (a) observations with negative equity and with stock price below $1, (b) financial firms and public utilities (SIC 6000–6999 and 4900–4999) due to differences in financial accounting regulations, (c) observations with missing cost data, and (d) observations with missing accounting and disaster data. Furthermore, we exclude observations in which SGA exceeds sales, as these cases represent economically implausible outliers in which SGA values do not reflect meaningful underlying cost behaviour. We also trim the top and bottom 1% of observations with extreme values in the accounting data used to run the main model. This results in a final sample of 66,551 firm-year observations covering 7,981 unique firms from 1993 to 2019.

Table 2 reports the sample distribution by state and industry (SIC 1 digit). California has the largest number of observations (10,330), followed by Texas (7,020) and New York (5,048), while Alaska, Wyoming, North Dakota, Puerto Rico, New Mexico, South Dakota, and Montana have fewer than 50 observations. This distribution is consistent with the economic relevance of the US states. Furthermore, we see that the largest number of observations are in Manufacturing (SIC 2 and 3) and Services (SIC 7 and 8). The lowest number of observations reported among the different sectors is in the Public Administration (SIC 9) and Agriculture, Forestry and Fishing (SIC 0) sectors.

3.2. *Measure of natural disasters and geographical proximity*

Information regarding natural disasters is obtained from the FEMA database. This database includes declared disasters that materially affect local economies and provides information on the incident type, beginning date, ending date, and impacted area (identified by state, county, and place code). Correspondingly, we consider floods (coastal, flash, and lakeshore floods), hurricanes (typhoons, tropical depressions, tropical storms, and storm surges), tornadoes (funnel

Table 1. Sample selection.

	Sample observations
The universe of firm-year observations of U.S. incorporated companies with ZIP Code, total assets and employee data available (and not negative) in COMPUSTAT North America during the period 1993–2019	157,137
Reason for dropping	**Obs. dropped**
Negative equity	16,002
Stock price is below 1$	9,916
SIC code is 6000–6999 and 4900–4999	35,044
Missing accounting data related to Sale, SGA, COGS	21,356
SGA higher than Sale (current and previous periods)	4,359
Missing Disaster data	637
Missing Accounting data	3,272
Final sample	**66,551** [t = 1993–2019] [7,981 firms]

Notes: Accounting variables used in the main analyses are trimmed at the 1st and 99th percentiles. The resulting exclusions are reflected in the sample selection steps 'Missing accounting data related to Sale, SGA, COGS' and 'Missing Accounting data'.

Table 2. Sample distribution by state & industry (sic1-digit code).

State code	State	SIC = 0	SIC = 1	SIC = 2	SIC = 3	SIC = 4	SIC = 5	SIC = 7	SIC = 8	SIC = 9	Total
AK	Alaska	0	0	0	0	7	4	0	0	0	11
AL	Alabama	0	48	48	131	31	77	36	15	0	386
AR	Arkansas	0	20	63	33	32	94	12	0	0	254
AZ	Arizona	0	124	141	419	31	142	127	59	2	1,045
CA	California	94	224	1,065	5,162	206	1,038	2,085	353	103	10,330
CO	Colorado	8	446	263	423	201	157	288	83	0	1,869
CT	Connecticut	0	23	195	773	44	107	213	81	13	1,449
DC	District of Columbia	0	0	6	28	18	0	20	36	4	112
DE	Delaware	0	6	83	43	11	5	31	1	2	182
FL	Florida	31	126	356	887	227	696	505	174	16	3,018
GA	Georgia	0	92	454	376	153	263	581	130	6	2,055
HI	Hawaii	16	34	25	0	53	0	9	0	0	137
IA	Iowa	6	0	107	116	3	40	14	0	0	286
ID	Idaho	0	33	17	30	0	28	2	12	0	122
IL	Illinois	6	90	685	1,368	236	547	312	158	17	3,419
IN	Indiana	5	21	166	467	30	120	56	38	0	903
KS	Kansas	0	28	34	99	25	37	84	50	27	384
KY	Kentucky	0	8	94	94	0	81	24	59	8	368
LA	Louisiana	0	70	39	40	66	52	25	72	3	367
MA	Massachusetts	0	9	367	1,794	39	250	760	241	33	3,493
MD	Maryland	0	38	173	158	60	96	188	120	0	833
ME	Maine	0	0	39	15	0	7	11	0	0	72
MI	Michigan	0	11	239	864	38	109	134	27	17	1,439
MN	Minnesota	0	28	411	1,016	47	390	306	68	6	2,272
MO	Missouri	18	62	210	366	5	143	165	9	0	978
MS	Mississippi	37	0	32	9	13	17	6	0	0	114
MT	Montana	0	3	1	17	8	5	15	0	0	49
NC	North Carolina	20	34	331	513	70	365	110	81	50	1,574
ND	North Dakota	0	12	4	2	0	16	2	0	0	36
NE	Nebraska	0	4	32	92	4	60	53	5	16	266
NH	New Hampshire	0	0	47	156	0	62	29	0	1	295
NJ	New Jersey	3	6	735	833	106	421	391	205	44	2,744
NM	New Mexico	0	11	0	16	0	9	2	3	0	41

(*Continued*)

Table 2. Continued.

State code	State	SIC = 0	SIC = 1	SIC = 2	SIC = 3	SIC = 4	SIC = 5	SIC = 7	SIC = 8	SIC = 9	Total
NV	Nevada	0	5	25	120	19	27	326	3	12	537
NY	New York	2	84	1,132	1,574	395	744	865	210	42	5,048
OH	Ohio	29	105	472	1,122	51	561	160	101	0	2,601
OK	Oklahoma	0	291	42	112	11	74	25	16	4	575
OR	Oregon	0	0	122	423	12	76	93	6	4	736
PA	Pennsylvania	11	92	511	1,140	82	441	317	121	15	2,730
PR	Puerto Rico	11	0	0	9	0	0	13	3	0	36
RI	Rhode Island	0	0	22	167	33	46	21	0	0	289
SC	South Carolina	0	1	111	91	4	64	34	13	0	318
SD	South Dakota	0	0	5	30	4	0	0	7	0	46
TN	Tennessee	3	20	216	163	42	323	102	167	0	1,036
TX	Texas	0	1,932	868	1,552	352	1,211	841	210	54	7,020
UT	Utah	0	29	160	204	25	42	111	30	3	604
VA	Virginia	0	31	266	283	153	227	388	235	0	1,583
VT	Vermont	0	10	16	13	0	7	19	0	0	65
WA	Washington	27	13	140	355	112	204	231	12	7	1,101
WI	Wisconsin	3	0	211	736	38	116	113	4	0	1,221
WV	West Virginia	0	17	18	16	0	0	29	9	0	89
WY	Wyoming	0	7	0	0	6	0	0	0	0	13
		330	4,248	10,799	24,450	3,103	9,601	10,284	3,227	509	66,551

Notes: SIC = 0 Agriculture, Forestry and Fishing; SIC = 1 Mining & Construction; SIC = 2 & 3 Manufacturing; SIC = 4 Transportation, Communications, Electric, Gas and Sanitary service; SIC = 5 Wholesale & Retail trade; SIC = 6 Finance, Insurance and Real Estate; SIC = 7 & 8 Services; SIC = 9 Public Administration.

clouds and waterspouts), tsunamis, landslides, and wildfires. All disaster events in our sample meet the statutory thresholds for federal disaster assistance under the Stafford Act and therefore represent material events for the affected local communities, although there is substantial heterogeneity in severity, ranging from large-scale events (e.g. Katrina-type disasters) to smaller but still economically meaningful shocks.

The FEMA disaster dataset comprises 3,450 distinct disaster declarations, with each declared event affecting, on average, 45 counties. The most prevalent disaster types are wildfires and severe storms, each accounting for approximately 27% of all events, followed by floods (21%) and hurricanes (9%). There are notable regional differences: wildfires dominate in states such as New Mexico and Nevada, while severe storms are more prevalent in Alabama and hurricanes in Florida. With respect to severity, 64% of all declarations are classified as Major Disasters (DR), while only 10% are Emergency Declarations (EM); the remaining declarations primarily relate to fire management assistance. Under the Stafford Act, a Major Disaster (DR) declaration authorises broad federal assistance to individuals, public entities, and mitigation programmes in response to large-scale events. By contrast, an Emergency Declaration (EM) applies to events that do not meet the threshold for a major disaster but nevertheless require federal support for immediate response and recovery. These patterns highlight both the scale and the heterogeneity of disaster exposure in our sample.

Figure 1 shows the average annual number of natural disasters at the county level. The degree of colour intensity indicates the degree of a county's exposure to natural disasters. Figure 2 presents the annual number of disasters. While this figure captures the temporal variation in the occurrence of natural disasters, the overall trend reveals a clear increase over time across the US, consistent with previously documented patterns (Lindsay and McCarthy 2012, Dapena 2018, Smith 2020). This highlights the increasing significance that these events are likely to have for citizens and corporations.

From the raw declaration summary, we remove events with missing county information and events with the same declaration date, event title, and geographical area impacted but different declaration types – retaining the most severe declaration in such cases, as

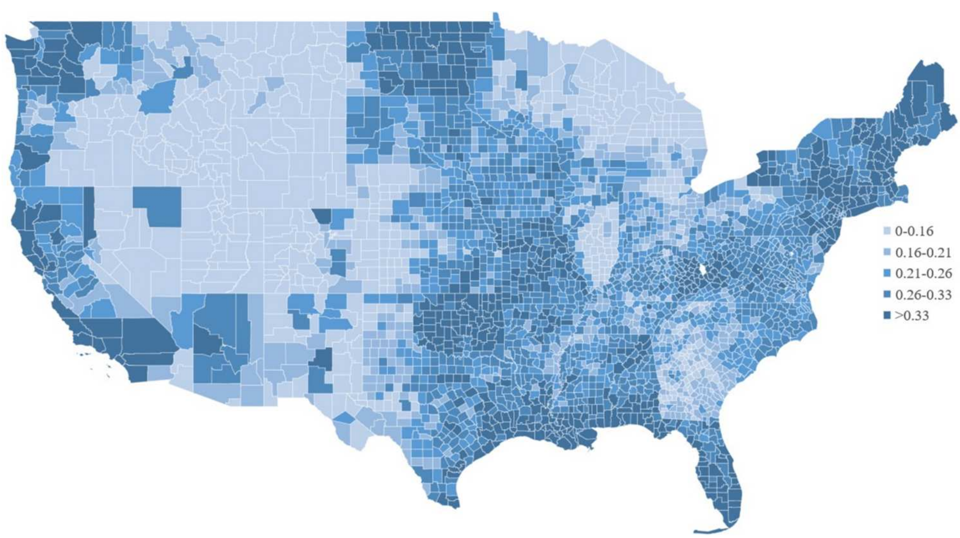

Figure 1. Average number of annual natural disasters across counties between 1965 and 2019.
Notes: This figure presents the total number of disasters by U.S. County over the period 1965–2019. Disaster declaration is retrieved from the FEMA dataset.

lower-severity types typically represent preliminary assessments later upgraded to a higher severity level for the same underlying disaster. We consider an array of extreme weather events instead of focusing on a single type of event. This approach makes our results more generalisable to US firms overall because our broad set of events affects firms throughout the US. In contrast, only a subset of firms is directly exposed to certain types of events (e.g. hurricanes).

To operationalise disaster exposure, we construct two indicator variables capturing whether firms are directly affected by a natural disaster (*HIT*) or are located near one (*NEIGHBOR*). We begin by counting the number of FEMA-declared disasters within a rolling 12-month window at the county level. A county is classified as affected (*HIT*) if it experiences one or more disasters during the prior 12 months, and zero otherwise.

To capture geographic spillovers, we identify neighbouring counties based on physical distance. Specifically, for each affected county, we match it to its ten closest unaffected counties using great-circle distance computed from county latitude and longitude coordinates obtained from the National Weather Service (https://www.weather.gov/gis/ZoneCounty). Firms headquartered in these matched counties are classified as *NEIGHBOR*. All remaining firms (i.e. those headquartered in counties that are neither directly affected nor matched as neighbours) form the control group.

This approach allows us to separately identify the cost responses of firms exposed to direct disaster shocks and those exposed only to proximity-based effects.

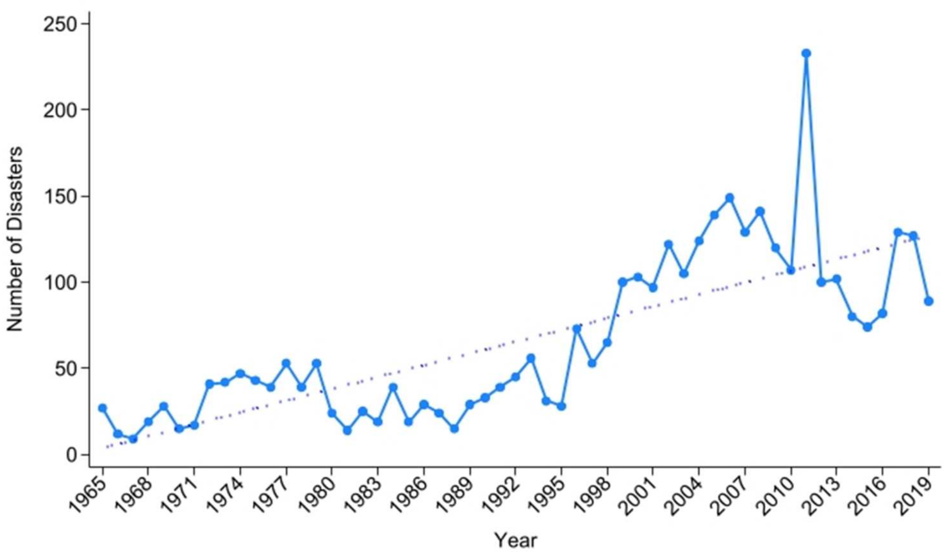

Figure 2. Total disasters over time.
Notes: This figure shows the annual number of disasters during our sample period (1993–2019). Data are obtained from the FEMA dataset. The graph is based on the following incident types: Coastal Storm, Drought, Fire, Flood, Freezing, Hurricane, Severe Ice Storm, Severe Storm(s), Snow, Tornado, Tsunami, and Typhoon.

Empirical model

Most studies on cost management follow the cross-sectional model introduced by Anderson et al. (2003), enabling the measurement of cost responses to contemporaneous changes in sales revenue and distinguishing between periods with revenue increases and those with decreases. The model in its original form (Anderson et al. 2003) is as follows:

$$\Delta lnCOSTS = \beta_0 + \beta_1 \, \Delta lnSALES + \beta_2 \, DEC \times \Delta lnSALES + \varepsilon_t \tag{1}$$

where: $\Delta lnCOSTS$ denotes the log-change in either selling, general, and administrative costs or costs of goods sold for firm *i* in year *t*, $\Delta lnSALES$ is the log-change in sales, approximating the firm's activity level, and *DEC* is an indicator variable that equals one if sales decrease between two fiscal years and zero otherwise. Using log specifications and ratios improves comparability across firms and helps mitigate potential heteroscedasticity (see Anderson et al. 2003). Moreover, log specifications enable a straightforward interpretation of coefficient values as percentage changes in costs. The coefficient β_1 measures the average percentage growth in costs when sales increase by 1% and the sum of β_1 and β_2 measures the average percentage decline for a 1% decrease in sales. Accordingly, if β_2 is significantly negative (positive), it indicates asymmetric, (anti-)sticky cost behaviour, given a positive value of β_1.

To provide a comprehensive picture of how natural disasters affect cost management decisions, we consider two different cost categories. Prior literature focusing on the role of psychological biases and managerial expectations/opportunism in cost management has predominantly examined SGA costs (e.g. Chen et al. 2012, 2022), which include expenses such as sales and marketing, administrative salaries, and insurance costs. These costs are considered more discretionary because they are not directly tied to core operations and can be adjusted more easily in response to changing business conditions. In contrast, costs like COGS are more directly linked to short-term production, market developments, and supply chain dynamics, encompassing raw materials, labour, and manufacturing costs.[3]

To test our hypotheses, we augment the original model by Anderson et al. (2003) as follows:[4]

$$\begin{aligned}\Delta lnCOSTS = {} & \beta_0 + \beta_1 \Delta lnSALES + \beta_2 \, DEC \\ & + (\beta_3 \, HIT + \beta_4 \, NEIGHBOR + \beta_5 \, AI + \beta_6 \, EI + \beta_7 \, CF + \beta_8 \, SUC\_DEC) \\ & \times \Delta lnSALES \times DEC \\ & + (\beta_9 \, HIT + \beta_{10} \, NEIGHBOR + \beta_{11} \, AI + \beta_{12} \, EI + \beta_{13} \, CF + \beta_{14} \, SUC\_DEC) \\ & \times \Delta lnSALES \\ & + (\beta_{15} \, HIT + \beta_{16} \, NEIGHBOR + \beta_{17} \, AI + \beta_{18} \, EI + \beta_{19} \, CF + \beta_{20} \, SUC\_DEC) \\ & + FE + \varepsilon_t \end{aligned} \tag{2}$$

Using *HIT* and *NEIGHBOR,* we include two disaster-related variables in model (2). We distinguish between firms in US counties directly hit by natural disasters (*HIT*) and those located near directly affected counties (*NEIGHBOR*), as explained in the course of our hypothesis

[3]We do not examine Operating Costs as aggregating COGS and SGA might obscure distinct underlying patterns in cost behavior.
[4]All variables are defined in the Appendix.

development.[5] Hence, the variable of main interest is *NEIGHBOR* and its three-way interaction term with *DEC* and the change in sales (*ΔlnSALES*), as well as the two-way interaction term with *ΔlnSALES*. *NEIGHBOR* is defined as a dummy variable that takes the value of one if the firm's headquarters is located in a county close to the location of a natural disaster in the previous 12 months and zero otherwise. As shown in model (2), our coefficients of interest are β_4 and β_{10}, which measure the cost management of neighbouring firms in response to a sales decline/increase. Following our hypothesis, we expect to find a positive coefficient for β_4 and a negative coefficient for β_{10}, indicating that managers of neighbouring firms increase costs less in response to a sales increase and reduce them more following a sales decrease.

We closely follow established cost stickiness literature (e.g. Chen et al. 2012) in selecting our control variables for our baseline model (2), which we later extend with additional controls. Specifically, we control for asset (*AI*) and employee intensity (*EI*) as proxies for the level of adjustment costs. We also control for free cash flow (*CF*) as a proxy for opportunistic managerial motives, while *SUC_DEC* controls for managers' perceptions, because executives are likely to consider negative demand shocks more permanent after two consecutive downturns, which mitigates cost stickiness (Banker et al. 2014). Across different specifications, we employ various combinations of fixed effects to account for unobserved state-, county-, industry-, and year-specific variation in costs and sales. Furthermore, we cluster standard errors at the firm level (Banker et al. 2013).

4. Empirical results

4.1. *Descriptive statistics*

Panel A of Table 3 presents descriptive statistics for the variables used in our main test. The average change in costs is 9.3% (*ΔlnSGA)* and 9.4% (*ΔlnCOGS)*, with standard deviations of 19.5% and 24.0%, respectively. Considering the change in sales (*ΔlnSALES*), we find an average change of 9.1% with a standard deviation of 22.4%.

Because *HIT* and *NEIGHBOR* are defined at the county level, their descriptive statistics depend on the distribution of firms across counties rather than the proportion of counties experiencing disasters. Accordingly, in our sample, the firm-year mean of *HIT* is 0.391, and the firm-year mean of *NEIGHBOR* is 0.231. Hence, natural disasters with material consequences regularly hit firms in the US, which is why they are likely to affect firms' cost management.

Panel B of Table 3 reports the same descriptive statistics presented in Panel A, but separately for *HIT*, *NEIGHBOR*, and firms that are neither hit nor neighbouring. The mean change in sales is slightly higher for *HIT* firms ($p < 0.05$). Similarly, the mean change in costs is higher for *HIT* firms than for both *NEIGHBOR* firms and distant firms ($p < 0.01$). In contrast, the mean asset intensity and cash flow are lower for *HIT* than for *NEIGHBOR* firms ($p < 0.01$). *NEIGHBOR* firms and distant firms, however, exhibit no meaningful differences in the change in sales, the change in costs, or cash flow. In untabulated analyses, we also compare changes in sales and costs for *HIT* firms in the years $t-1$ and $t+1$ surrounding a natural disaster at t. We find that both changes in sales and costs decline in $t+1$ relative to $t-1$, consistent with the disruptive effects of disaster exposure on firms in directly affected regions. For neighbouring firms, we

[5]It is important to note that we cannot clearly identify the firms that were affected by a natural disaster. Accordingly, some firms in counties directly hit by a natural disaster might not be directly impacted, which is why the same arguments as for neighbouring firms apply. Therefore, although we measure the occurrence of a natural disaster at the granular county level, HIT and NEIGHBOR are not perfectly separate.

Table 3. Descriptive statistics.

Panel A: Full Sample

Variable	Obs.	Mean	Std. Dev.	Q1	Q25	Median	Q75	Q99
ΔlnSALES	66,551	0.091	0.224	−0.522	−0.012	0.075	0.183	0.801
ΔlnSGA	66,551	0.093	0.195	−0.389	−0.008	0.073	0.173	0.745
ΔlnCOGS	66,551	0.094	0.240	−0.564	−0.014	0.076	0.188	0.884
DEC	66,551	0.277	0.448	0	0	0	1	1
HIT	66,551	0.391	0.488	0	0	0	1	1
NEIGHBOR	66,551	0.231	0.422	0	0	0	0	1
AI	66,551	1.226	1.140	0.280	0.639	0.932	1.419	5.347
EI	66,551	0.007	0.007	0.001	0.003	0.005	0.008	0.037
CF	66,551	0.067	0.098	−0.266	0.025	0.073	0.121	0.276
SUC_DEC	66,551	0.264	0.441	0	0	0	1	1

Panel B: HIT, NEIGHBOR, and Control sub-samples

Sample	(1): HIT		(2): NEIGHBOR		(3): CONTROL		Difference (t-stat)		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	1 vs. 2	1 vs. 3	2 vs. 3
$\Delta lnSALES_{t+1}$	0.076	0.235	0.070	0.227	0.067	0.232	2.19**	4.01***	1.32
ΔlnSALES	0.095	0.225	0.090	0.223	0.088	0.223	2.19**	3.2***	0.58
ΔlnSGA	0.097	0.197	0.089	0.193	0.090	0.194	4.22***	4.18***	−0.58
ΔlnCOGS	0.098	0.241	0.091	0.238	0.091	0.240	3.21***	3.31***	−0.32
DEC	0.266	0.442	0.280	0.449	0.286	0.452	−2.90***	−5.02***	−1.46
HIT	1	0	0	0	0	0	n.a.	n.a.	n.a.
NEIGHBOR	0	0	1	0	0	0	n.a.	n.a.	n.a.
AI	1.220	1.130	1.248	1.209	1.218	1.105	−2.41**	0.19	2.58***
EI	0.007	0.007	0.006	0.007	0.007	0.008	5.57***	−0.07	−5.42***
CF	0.066	0.101	0.068	0.097	0.067	0.096	−2.04**	−1.02	1.18
SUC_DEC	0.253	0.435	0.270	0.444	0.271	0.444	−3.92***	−4.65***	−0.14

Panel C: Correlation analysis

		1	2	3	4	5	6	7	8	9	10
ΔlnSALES	1	1									
ΔlnSGA	2	0.679*	1								
ΔlnCOGS	3	0.869*	0.608*	1							
DEC	4	−0.638*	−0.427*	−0.550*	1						
HIT	5	0.013*	0.019*	0.015*	−0.019*	1					
NEIGHBOR	6	−0.004	−0.010*	−0.008	0.003	−0.440*	1				
AI	7	0.01	0.061*	0.037*	0.039*	−0.004	0.011*	1			
EI	8	0.019*	0.031*	0.025*	−0.017*	0.010*	−0.023*	−0.080*	1		
CF	9	0.079*	0.002	0.026*	−0.137*	−0.007	0.007	−0.045*	−0.004	1	
SUC_DEC	10	−0.173*	−0.241*	−0.187*	0.219*	−0.020*	0.008	0.034*	−0.017*	−0.127*	1

Notes: The full sample consists of 66,551 firm-year observations. Of these, 26,054 observations are classified as HIT,15,395 as NEIGHBOR, and 25,102 as CONTROL (i.e. firms not identified as either HIT or NEIGHBOR). See Appendix for variable definitions. * indicates statistical significance at the 0.01 levels (two-tailed).

also find that both changes in sales and costs decline in t + 1 relative to t−1, suggesting that there are, at least to some extent, indirect disruptive effects of disaster exposure on firms operating in economically connected but not directly affected regions. The magnitude of the decline is, however, smaller than that observed for HIT firms. Taken together, these descriptive patterns do not indicate any clear, economically grounded rationale for *NEIGHBOR* firms to adjust their costs differently from geographically distant firms. We further investigate this point in the following sections using more formal econometric tests.

Panel C of Table 3 presents the univariate correlation analysis using Pearson coefficients. The correlations suggest that *HIT* firms tend to experience increases in both sales (coefficient is 0.013, with $p < 0.01$) and costs (coefficients for *ΔlnSGA* and *ΔlnCOGS* are 0.019 and 0.015, respectively, both with $p < 0.01$). In contrast, *NEIGHBOR* firms exhibit a negative correlation primarily with *ΔlnSGA* (coefficient is −0.010, with $p < 0.01$). However, these simple associations cannot provide a meaningful test of asymmetric cost behaviour because they do not account for changes in sales, firm characteristics, or contextual factors. A proper assessment, therefore, requires the multivariate framework presented in the next section.

4.2. *Main results*

Table 4 presents the regression results for our main model specifications for COGS and SGA. To assess the robustness of our findings, we estimate four different specifications. Columns 1 and 2 report results using only the standard set of controls employed in the asymmetric cost-behaviour literature (AI, EI, CF, and SUC_DEC), as described in Section III. These baseline specifications follow the conventional structure used in Banker and Byzalov (2014) and related studies. Columns 3 and 4 augment the baseline model with interactions between Year and State fixed effects and both *ΔlnSALES* and *DEC* × *ΔlnSALES*. This extension directly responds to a potential concern that the secular increase in the incidence of natural disasters (also see Figure 2) may coincide with unrelated trends in cost stickiness (e.g. technological or organisational change), and that geographic heterogeneity in cost behaviour may confound our estimates. Following Filip et al. (2025), we therefore include *ΔlnSALES* × Year FE, *DEC* × *ΔlnSALES* × Year FE, *ΔlnSALES* × State FE, *DEC* × *ΔlnSALES* × State FE. These interactions flexibly absorb systematic time-series variation and cross-state differences in the level of cost stickiness unrelated to disaster exposure. Columns 5 and 6 present a specification with additional firm-level controls frequently used in recent cost-behaviour applications, namely leverage, size, market-to-book value, loss, and target indicators (Filip et al. 2025). Finally, Columns 7 and 8 report a specification that additionally incorporates board characteristics (i.e. board age, tenure, board size, and fixed pay). As expected, in Columns 5–8, the sample size decreases due to the limited availability of additional controls.

For neighbouring firms, the two-way interaction *ΔlnSALES* × *NEIGHBOR* is generally insignificant across specifications and cost categories, with the exception of a small negative coefficient for *ΔlnSGA* in Column 2. This pattern suggests that, relative to other firms, *NEIGHBOR* firms do not exhibit a meaningfully different baseline cost response when sales increase; if anything, the weakly negative coefficient reported above points to slightly more cautious additions of discretionary resources in expanding periods. The picture changes when we consider the three-way interaction *DEC* × *ΔlnSALES* × *NEIGHBOR*, which captures the incremental cost response to sales decreases, the central focus in cost stickiness research (Anderson et al. 2003). For *ΔlnCOGS*, this coefficient is insignificant in Columns 1 and 3 and only marginally significant at the 10% level in Columns 5 and 7, suggesting no robust evidence of differences in production-related cost adjustments. In contrast, for *ΔlnSGA*, the three-way interaction is positive and statistically significant across all specifications, implying that *NEIGHBOR* firms cut SGA

Table 4. Cost management reactions to natural disasters.

	(1) ΔlnCOGS	(2) ΔlnXSGA	(3) ΔlnCOGS	(4) ΔlnXSGA	(5) ΔlnCOGS	(6) ΔlnXSGA	(7) ΔlnCOGS	(8) ΔlnXSGA
Constant	0.0093***	0.0161***	0.0735***	−0.0612***	0.0676***	−0.0477***	−0.0260*	0.0115
	[3.84]	[5.68]	[4.04]	[4.81]	[3.57]	[3.02]	[1.72]	[0.45]
ΔlnSALES	1.0037***	0.7340***	−1.4727**	1.4495***	−1.7838**	1.3960***	1.1030***	0.7052***
	[78.12]	[52.47]	[2.09]	[8.09]	[2.56]	[4.07]	[9.83]	[3.72]
DEC × ΔlnSALES	−0.0367	−0.4061***	3.4586***	−1.0081***	3.6903***	−0.9238**	−0.0657	−0.1093
	[1.20]	[14.34]	[4.44]	[5.02]	[4.78]	[2.53]	[0.26]	[0.29]
ΔlnSALES × HIT	**0.0059**	**0.0005**	**0.0105**	**0.0056**	**0.0107**	**0.0024**	**−0.0254**	**−0.0066**
	[0.60]	**[0.04]**	**[1.06]**	**[0.43]**	**[1.06]**	**[0.18]**	**[1.34]**	**[0.37]**
DEC × ΔlnSALES × HIT	**−0.0555****	**0.0147**	**−0.0306**	**0.0218**	**−0.0222**	**0.0259**	**−0.0157**	**0.0434**
	[1.99]	**[0.58]**	**[1.14]**	**[0.85]**	**[0.82]**	**[0.98]**	**[0.34]**	**[1.06]**
ΔlnSALES × NEIGHBOR	**−0.0129**	**−0.0260***	**−0.0097**	**−0.0167**	**−0.0101**	**−0.0207**	**−0.0100**	**−0.0194**
	[1.10]	**[1.72]**	**[0.85]**	**[1.08]**	**[0.89]**	**[1.36]**	**[0.58]**	**[0.96]**
DEC × ΔlnSALES × NEIGHBOR	**0.0124**	**0.0787*****	**0.0412**	**0.0674****	**0.0548***	**0.0740****	**0.0800***	**0.0812***
	[0.41]	**[2.71]**	**[1.36]**	**[2.22]**	**[1.78]**	**[2.38]**	**[1.82]**	**[1.89]**
DEC × ΔlnSALES × AI	−0.0427***	−0.0192**	−0.0292**	−0.0193**	−0.0249	−0.0097	−0.0627**	−0.0322*
	[2.78]	[2.06]	[2.07]	[2.18]	[1.62]	[0.90]	[2.17]	[1.90]
DEC × ΔlnSALES × EI	0.2653	0.6681	−1.8495	1.4759	−1.4005	1.5578	−0.3129	−2.8388
	[0.19]	[0.35]	[1.51]	[0.77]	[1.03]	[0.75]	[0.15]	[0.86]
DEC × ΔlnSALES × CF	0.1527*	0.2886***	0.2180***	0.2254**	0.1805**	0.1352	0.1912	0.3880**
	[1.87]	[3.11]	[2.66]	[2.44]	[1.97]	[1.34]	[0.91]	[1.99]
DEC × ΔlnSALES × SUC_DEC	0.2096***	0.3583***	0.1821***	0.3217***	0.1716***	0.2992***	0.1675***	0.2707***
	[7.99]	[13.99]	[7.12]	[12.29]	[6.66]	[11.21]	[3.41]	[6.55]
ΔlnSALES × AI	−0.0249***	−0.0196***	−0.0224***	−0.0126***	−0.0283***	−0.0248***	−0.0218	−0.0218**
	[3.31]	[3.96]	[3.06]	[2.77]	[3.45]	[4.29]	[1.44]	[2.40]
ΔlnSALES × EI	2.2262***	2.3355**	1.9941***	1.3847	1.8711***	1.8367**	1.2515*	4.8529***
	[5.38]	[2.55]	[4.73]	[1.54]	[4.29]	[2.08]	[1.74]	[3.88]
ΔlnSALES × CF	−0.1597***	−0.0454	−0.1369***	0.0320	−0.1280***	−0.0295	−0.1786*	−0.1921*
	[3.79]	[0.90]	[3.37]	[0.66]	[2.89]	[0.56]	[1.71]	[1.87]
ΔlnSALES × SUC_DEC	−0.0929***	−0.2090***	−0.0863***	−0.1900***	−0.0799***	−0.1562***	−0.1018***	−0.1362***
	[7.67]	[13.81]	[7.02]	[12.22]	[6.31]	[10.24]	[4.14]	[5.97]
HIT	−0.0019	0.0024	−0.0022	0.0015	−0.0019	0.0024	0.0017	0.0026
	[1.16]	[1.25]	[1.42]	[0.77]	[1.20]	[1.21]	[0.68]	[1.09]

(*Continued*)

Table 4. Continued.

	(1) ΔlnCOGS	(2) ΔlnXSGA	(3) ΔlnCOGS	(4) ΔlnXSGA	(5) ΔlnCOGS	(6) ΔlnXSGA	(7) ΔlnCOGS	(8) ΔlnXSGA
NEIGHBOR	0.0002	0.0040*	0.0007	0.0025	0.0008	0.0032	0.0027	0.0020
	[0.13]	[1.78]	[0.40]	[1.12]	[0.46]	[1.42]	[1.20]	[0.76]
AI	0.0032*	0.0101***	0.0039**	0.0090***	0.0043**	0.0098***	0.0060*	0.0117***
	[1.86]	[6.37]	[2.55]	[6.08]	[2.52]	[5.89]	[1.92]	[5.38]
EI	0.0063	−0.0617	−0.0346	0.0728	−0.0453	0.0963	0.0071	−0.4649**
	[0.07]	[0.40]	[0.44]	[0.50]	[0.59]	[0.66]	[0.07]	[2.47]
CF	−0.0916***	−0.0518***	−0.0898***	−0.0599***	−0.0437***	−0.0479***	−0.0526***	0.0667***
	[10.52]	[4.58]	[10.57]	[5.49]	[4.62]	[4.06]	[2.83]	[3.54]
SUC_DEC	−0.0060***	−0.0270***	−0.0065***	−0.0292***	−0.0100***	−0.0292***	−0.0064**	−0.0158***
	[3.68]	[13.54]	[3.99]	[14.45]	[5.98]	[14.22]	[2.39]	[6.09]
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	No	No	No	No	No	No
State Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Additional (DEC × ΔlnSALES) × FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Additional firm-level controls	No	No	No	No	Yes	Yes	Yes	Yes
Additional board-level controls	No	No	No	No	No	No	Yes	Yes
Observations	66,551	66,551	66,551	66,551	63,209	63,209	28,112	28,112
Adjusted R^2	0.767	0.516	0.772	0.521	0.777	0.533	0.757	0.583

Notes: Variable definitions are in the Appendix. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on standard errors clustered at the firm level.

costs more aggressively when sales decline. This heightened sensitivity in downturns is consistent with our hypothesis that nearby disasters trigger stronger discretionary cost adjustments among *NEIGHBOR* firms, despite the absence of direct operational damage. In the next subsection, we explore the mechanisms underlying this behaviour and examine whether the observed response pattern reflects rational managerial adjustments or a more irrational behavioural reaction to nearby disasters.

The coefficients for *HIT* firms follow a different pattern. The two-way interaction *ΔlnSALES* × *HIT* is consistently insignificant across all specifications, while the three-way interaction *DEC* × *ΔlnSALES* × *HIT* is also insignificant in all but one case (Column 1). This instability is consistent with the assumption that the cost structure of *HIT* firms is inherently difficult to predict, as firms in directly affected regions simultaneously face physical damage, operational disruptions, unusual demand, and cost shocks, and possibly substantial insurance proceeds or FEMA assistance. Because these forces push in different directions, systematic cost patterns are unlikely to emerge.

4.3. *Mechanism identification*

An inherent challenge in interpreting firms' responses to nearby natural disasters is distinguishing rational managerial adjustments from behavioural (irrational) reactions. Neighbouring firms may rationally reassess future demand, climate risk, or supply-chain reliability following a disaster, even in the absence of direct physical damage. At the same time, managers may react through a salience-driven channel and exhibit excessive pessimism that is not fully justified by fundamentals. More generally, natural disasters can affect cost behaviour through multiple mechanisms: (a) physical damage and operational disruptions, often accompanied by insurance payouts or government assistance; (b) rational pessimism about future demand; and (c) irrational pessimism driven by salience. While it is empirically difficult to cleanly separate these channels at the firm level, in this section we provide additional evidence aimed at identifying the dominant mechanisms underlying the *NEIGHBOR* results.

As a first step in distinguishing between physical and behavioural channels, we recall the descriptive evidence on sales and cost dynamics presented in Panel B of Table 3. In the disaster year, *HIT* firms exhibit higher sales and cost growth than both *NEIGHBOR* and distant firms, along with lower asset intensity and cash flow. By contrast, *NEIGHBOR* firms are indistinguishable from distant firms in sales, costs, and cash flow. These patterns suggest that *NEIGHBOR* firms have no clear economic reason to adjust costs differently and thus seem to exclude the mechanism described under (a).

To further isolate the mechanism, we examine whether disaster exposure rationally predicts future disaster risk. In Column 1 of Table 5, we regress *FUTURE_HIT* on current *HIT* and *NEIGHBOR*. This specification excludes firm-level controls and industry fixed effects, as disaster exposure varies at the county level, and standard errors are clustered by county. Consistent with prior evidence on the absence of systematic trends in disaster strikes (Dessaint and Matray 2017), we find a negative and significant association between *HIT* and *FUTURE_HIT*, while *NEIGHBOR* does not predict future disaster occurrence. This implies that managers in both directly affected and neighbouring counties have no rational reason to revise their beliefs about the likelihood of future disasters upward, which effectively rules out the mechanism described under (b).

In Column 2 of Table 5, we examine future sales growth for *HIT* and *NEIGHBOR* firms. We find that firms in directly affected regions exhibit no significant change in future sales, whereas neighbouring firms experience a significant increase. The dependent variable $\Delta lnSALES_{t+1}$ is measured as the log-change in sales, consistent with the transformations used in the main

Table 5. Natural disasters and cost management reactions (mechanism analysis).

Dep. Variable:	(1) HIT_{t+1}	(2) $\Delta lnSALES_{t+1}$
Constant	0.4023***	0.0160***
	[30.50]	[3.04]
HIT	**−0.0436****	**0.0013**
	[2.06]	**[0.57]**
NEIGHBOR	**−0.0167**	**0.0065*****
	[0.62]	**[2.62]**
AI		0.0325***
		[9.78]
EI		2.4235***
		[7.17]
CF		0.0823***
		[5.60]
SUC_DEC		−0.0296***
		[12.08]
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	No	Yes
County Fixed Effects	Yes	Yes
Observations	60,418	60,337
Adjusted R^2	0.166	0.090

Notes: Variable definitions are in the Appendix. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on standard errors clustered at county level and the firm level (respectively).

models. These results imply that managers of firms in directly affected counties have no rational basis for pessimism about future demand. In contrast, managers in neighbouring counties, if anything, have a rational basis for mild optimism (e.g. due to increased demand when neighbouring competitors are affected). This evidence rules out the rational pessimism channel. Accordingly, if the heightened downside cost sensitivity observed for *NEIGHBOR* firms reflects pessimism, it should stem from irrational, salience-driven beliefs rather than rational demand updating. This provides support for the mechanism described under (c).

To provide direct evidence of irrational pessimism, we examine management sales forecasts issued after a disaster using I/B/E/S data. Table 6 reports regressions of management sales guidance optimism (i.e. forecast minus actual sales) on *HIT* and *NEIGHBOR*. Columns 1 and 2 include only firm-years for which management guidance is available. Columns 3 and 4 expand the sample by including all firms and add an indicator variable equal to one when guidance is missing and zero otherwise. Across both specifications, we find that *NEIGHBOR* firms systematically underestimate subsequent sales relative to control firms and behave more like *HIT* firms than distant firms. This pattern provides direct evidence consistent with a salience-driven, irrational pessimism channel, rather than rational demand updating.

5. Additional analyses

5.1. *Natural disaster characteristics*

To assess the robustness of our main findings and to ensure that they are not driven by the specific construction of our geographical proximity measure or by the substantial heterogeneity in the nature of FEMA-declared events, we conduct a series of additional analyses that explicitly examine key disaster characteristics.

Table 6. Natural disasters and management Sales Guidance Optimism (SGO).

Dep. Variable:	(1) SGO	(2) SGO	(3) SGO	(4) SGO
HIT	**0.0124****	**0.0108****	**0.0014****	**0.0014****
	[2.47]	**[2.14]**	**[2.24]**	**[2.18]**
NEIGHBOR	**0.0128***	**0.0133***	**0.0020****	**0.0016***
	[1.94]	**[1.87]**	**[1.99]**	**[1.71]**
ROS	0.0224	0.0316	0.0013	0.0024
	[0.90]	[1.25]	[0.55]	[1.02]
SIZE	0.0328***	0.0018	0.0012*	0.0002
	[3.24]	[1.00]	[1.94]	[0.96]
LEV	0.0238	0.0274*	0.0003	0.0030*
	[0.90]	[1.88]	[0.10]	[1.85]
MTB	0.0118***	0.0077***	0.0010**	0.0012***
	[2.61]	[3.82]	[2.07]	[4.02]
LOSS	0.0066	0.0064	0.0007	0.0013
	[0.93]	[0.77]	[0.91]	[1.41]
MISSING_DUMMY			0.0103***	0.0064**
			[2.73]	[2.33]
Constant	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	Yes	No	Yes
County Fixed Effects	No	Yes	No	Yes
Firm Fixed Effects	Yes	No	Yes	No
Observations	8,351	8,351	64,382	64,382
Adjusted R^2	0.339	0.067	0.062	0.004

Notes: Variable definitions are in the Appendix. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on standard errors clustered at the firm level.

It is reasonable to expect that the effects of natural disasters are likely to intensify as the number of events in a region rises. Moreover, the psychological effects on managers in affected or neighbouring areas may be more pronounced when they witness multiple disasters within a short period, potentially amplifying firms' cost-adjustment responses. To capture this dimension, we refine our measure of disaster exposure by explicitly distinguishing between single and multiple disaster realizations within the same 12-month window. We construct the following indicators, capturing distinct disaster events, not different manifestations of the same event. *HIT_ONCE* (*HIT_MULTIPLE*) equals one if the firm's headquarters county experienced exactly one (more than one) natural disaster during the 12 months preceding the fiscal year-end, and zero otherwise. Analogously, *NEIGHBOR_ONCE* (*NEIGHBOR_MULTIPLE*) equals one if a neighbouring firm experienced exactly one (more than one) disaster during the same 12-month window, conditional on the firm not being directly affected. The firm-year mean of *HIT_ONCE* is 0.294, compared to 0.098 for *HIT_MULTIPLE*, indicating that only a relatively small fraction of firms experiences more than one disaster within the same 12-month window. A similar pattern emerges for neighbouring firms: the mean of *NEIGHBOR_ONCE* is 0.201, whereas *NEIGHBOR_MULTIPLE* is 0.003.[6]

[6]The proportions of *NEIGHBOR_ONCE* and *NEIGHBOR_MULTIPLE* do not sum to the total *NEIGHBOR* category because these subcategories are not mutually exclusive. A neighbouring county can be adjacent to a county hit by a first disaster, a second disaster, or both within the same 12-month window. Accordingly, the overall *NEIGHBOR* share reflects the union of these categories, not their sum.

We then replace *HIT* and *NEIGHBOR* in our baseline model with *HIT_ONCE*, *HIT_MULTIPLE*, *NEIGHBOR_ONCE*, and *NEIGHBOR_MULTIPLE*, and re-estimate the main regressions. The corresponding results are reported in Table 7. The two-way interactions are generally insignificant across cost categories. The only exception is a negative coefficient on *ΔlnSALES* × *NEIGHBOR_ONCE* in the SGA regression, which suggests that neighbouring firms exposed to a single nearby disaster add discretionary resources more cautiously during growth periods. The pattern becomes sharper when we jointly consider the three-way interactions. All such interactions are insignificant except for *DEC* × *ΔlnSALES* × *NEIGHBOR_ONCE*, which is strongly positive for SGA and positive for COGS. Interpreted together with the two-way effect, this joint pattern indicates that *NEIGHBOR_ONCE* firms do not accelerate cost additions when sales rise but cut both discretionary (i.e. SGA) and production-related (i.e. COGS) costs more aggressively when sales fall. Importantly, this asymmetric pattern emerges only for neighbouring firms exposed to a single disaster, while firms exposed to multiple nearby disasters exhibit no statistically reliable pattern. Overall, these results ensure that our main findings are not driven by multiple events repeatedly affecting a single county.

Another way to consider the frequency of disasters is to partition disaster exposure based on each county's historical disaster frequency, recognising that some regions are routinely exposed to specific disaster types (e.g. hurricanes and tornadoes in Florida), which may be perceived as relatively 'frequent' events. We define *HIT_FREQUENT* and *NEIGHBOR_FREQUENT* when a disaster type occurs with a frequency at or above the county-level median, and *HIT_RARE* and *NEIGHBOR_RARE* otherwise. The corresponding results are untabulated. Our main results are primarily driven by *NEIGHBOR_FREQUENT*. Interestingly, for both cost categories, *ΔlnSALES* × *HIT_RARE* is positive, while *DEC* × *ΔlnSALES* × *HIT_RARE* is negative, indicating that firms exposed to rare types of disasters expand costs more aggressively in upturns but cut them less sharply in downturns.

A further identification concern is that firms classified as NEIGHBOR in the current year may themselves have been exposed to natural disasters in earlier years, even if no disaster occurred in the preceding 12 months. If managers' cost behaviour were shaped by such prior disaster experience, our main *NEIGHBOR* effects could reflect lingering effects rather than contemporaneous proximity to a disaster. To address this alternative explanation, we explicitly model lagged disaster exposure. Specifically, we construct indicator variables *HIT_LAG1*, *HIT_LAG2*, *HIT_LAG3* and *NEIGHBOR_LAG1*, *NEIGHBOR_LAG2*, *NEIGHBOR_LAG3*, capturing whether a firm's headquarters county (or neighbouring county) was affected by a disaster one, two, or three years prior, respectively. We then extend our baseline specification by interacting *ΔlnSALES* and *DEC* × *ΔlnSALES* with both the current *HIT* and *NEIGHBOR* indicators and all lagged indicators, with all terms included concurrently in the same regression.

The results of this specification are reported in Table 8. Examining the contemporaneous effects, the two-way interactions for current *HIT* × *ΔlnSALES* and *NEIGHBOR* × *ΔlnSALES* remain insignificant, and our main result continues to hold: the three-way interaction *DEC* × *ΔlnSALES* × *NEIGHBOR* is positive and statistically significant for SGA only. This pattern confirms that our main finding is not affected by the inclusion of lagged disaster exposure. The additional insight from Table 8 concerns the role of one-year-lagged exposure. For neighbouring firms, the two-way interaction *ΔlnSALES* × *NEIGHBOR_LAG1* is negative and significant in the *COGS* regression, accompanied by a positive and significant coefficient on *DEC* × *ΔlnSALES* × *NEIGHBOR_LAG1*. Interpreted jointly, this pattern indicates that firms located near a disaster one year earlier become less willing to expand production-related resources when sales rise and more willing to cut them when sales fall. This reflects a more conservative adjustment of COGS that persists beyond the immediate disaster window. For firms in directly affected regions, the lagged pattern is even more symmetric. The two-way interaction

Table 7. Frequency of natural disasters and cost management reactions.

Dep. Variable:	(1) ΔlnCOGS	(2) ΔlnSGA
ΔlnSALES	1.0052***	0.7343***
	[79.17]	[53.16]
DEC × ΔlnSALES	−0.0497*	−0.4055***
	[1.67]	[14.55]
ΔlnSALES × HIT_ONCE	**0.0101**	**0.0023**
	[0.94]	**[0.18]**
ΔlnSALES × HIT_MULTIPLE	**−0.0109**	**−0.0059**
	[0.75]	**[0.32]**
DEC × ΔlnSALES × HIT_ONCE	**−0.0492**	**0.0263**
	[1.59]	**[0.96]**
DEC × ΔlnSALES × HIT_MULTIPLE	**−0.0187**	**−0.0191**
	[0.41]	**[0.52]**
ΔlnSALES × NEIGHBOR_ONCE	**−0.0177**	**−0.0292***
	[1.48]	**[1.84]**
ΔlnSALES × NEIGHBOR_MULTIPLE	**−0.0151**	**−0.0007**
	[0.22]	**[0.01]**
DEC × ΔlnSALES × NEIGHBOR_ONCE	**0.0494***	**0.0826*****
	[1.70]	**[2.74]**
DEC × ΔlnSALES × NEIGHBOR_MULTIPLE	**0.3611**	**0.0254**
	[1.21]	**[0.10]**
Three-way interaction terms control	Yes	Yes
Two-way interaction terms control	Yes	Yes
Single terms	Yes	Yes
Constant	Yes	Yes
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
County Fixed Effects	Yes	Yes
Observations	66,551	66,551
Adjusted R^2	0.767	0.516

Notes: Variable definitions are in the Appendix. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on standard errors clustered at the firm level.

ΔlnSALES × HIT_LAG1 is negative and significant for both SGA and COGS, while the corresponding three-way interaction *DEC × ΔlnSALES × HIT_LAG1* is positive for both cost categories. Jointly, these coefficients imply that firms in regions hit one year earlier increase costs less in upturns and reduce them more in downturns. This is consistent with a persistent tightening of resource commitments following direct exposure to a disaster.

While our main analysis does not explicitly model disaster severity, Section III provides relevant descriptive context: 64% of FEMA declarations in our sample are classified as Major Disasters (DR), while only 10% are Emergency Declarations (EM); the remainder relate to fire management assistance. Under the Stafford Act, DR declarations trigger broad and long-term federal assistance for large-scale events. In contrast, EM declarations apply to less severe events that require an immediate response and short-term support. In untabulated tests, we separately distinguish disaster exposure associated with DR and EM declarations. The estimates indicate that major disaster declarations primarily drive our main effects, while EM-related coefficients are generally insignificant.

Table 8. Natural disasters and cost management reactions (distributed lag analysis).

Dep. Variable:	(1) ΔlnCOGS	(2) ΔlnSGA
ΔlnSALES	1.0284*** [54.47]	0.7401*** [38.31]
DEC × ΔlnSALES	−0.0675 [1.55]	−0.4275*** [11.47]
ΔlnSALES × HIT	**0.0059** **[0.53]**	**−0.0044** **[0.33]**
ΔlnSALES × HIT_LAG1	−0.0240** [2.18]	−0.0301** [2.15]
ΔlnSALES × HIT_LAG2	−0.0113 [1.03]	−0.0011 [0.09]
ΔlnSALES × HIT_LAG3	0.0007 [0.07]	−0.0017 [0.13]
DEC × ΔlnSALES × HIT	**−0.0590**** **[1.97]**	**0.0234** **[0.89]**
DEC × ΔlnSALES × HIT_LAG1	0.1063*** [3.53]	0.0514* [1.92]
DEC × ΔlnSALES × HIT_LAG2	−0.0408 [1.43]	0.0005 [0.02]
DEC × ΔlnSALES × HIT_LAG3	0.0175 [0.65]	0.0254 [0.93]
ΔlnSALES × NEIGHBOR	**−0.0017** **[0.13]**	**−0.0165** **[0.99]**
ΔlnSALES × NEIGHBOR_LAG1	−0.0201* [1.74]	−0.0045 [0.29]
ΔlnSALES × NEIGHBOR_LAG2	−0.0030 [0.23]	0.0009 [0.05]
ΔlnSALES × NEIGHBOR_LAG3	−0.0124 [0.95]	−0.0160 [1.00]
DEC × ΔlnSALES × NEIGHBOR	**−0.0054** **[0.17]**	**0.0638**** **[2.06]**
DEC × ΔlnSALES × NEIGHBOR_LAG1	0.0766** [2.48]	−0.0049 [0.16]
DEC × ΔlnSALES × NEIGHBOR_LAG2	−0.0221 [0.68]	0.0105 [0.33]
DEC × ΔlnSALES × NEIGHBOR_LAG3	−0.0157 [0.43]	0.0478 [1.57]
Three-way interaction terms control	Yes	Yes
Two-way interaction terms control	Yes	Yes
Single terms	Yes	Yes
Constant	Yes	Yes
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
County Fixed Effects	Yes	Yes
Observations	62,596	62,596
Adjusted R^2	0.757	0.501

Notes: Variable definitions are in the Appendix. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels (two-tailed), respectively. t-statistics are presented in parentheses and are based on standard errors clustered at the firm level.

Managerial and regional characteristics

The response to natural disasters is likely shaped not only by economic exposure but also by managerial characteristics and the regional environment in which firms operate. These dimensions may provide additional insight into firms' cost responses beyond purely operational channels. Accordingly, we conduct a set of cross-sectional tests that examine whether variation in such characteristics moderates firms' reactions to nearby disasters. These analyses are intended to provide additional insight into the underlying mechanisms, rather than to redefine the main findings.

Climate-related beliefs may shape how local communities and, by extension, managers, perceive and react to natural disasters. To capture this dimension, we use county-level data from the Yale Climate Opinion Survey (Howe et al. 2015), based on the question: 'Do you think that global warming will harm people in the U.S.?' We classify counties as high-belief (above the median) or low-belief (below the median) in perceived climate risk. In untabulated tests, our main results are present only in high-belief counties, while they largely disappear in low-belief regions. This pattern is consistent with the interpretation that stronger climate-related beliefs increase the salience of nearby disasters and amplify firms' responses.

We also examine whether our results are sensitive to the inclusion of time-varying county-level characteristics, which may jointly affect disaster exposure and cost behaviour. Specifically, we control for county education, GDP per capita, and population. In untabulated tests, our main conclusions remain unchanged: the *NEIGHBOR* effect for SGA and the overall pattern of asymmetric cost responses continue to hold. The county-level controls themselves are largely insignificant, indicating that our findings are not driven by local economic or demographic conditions.

Managerial characteristics may further shape how executives interpret and respond to natural disasters. To explore this dimension, we examine board tenure as a proxy for managerial experience, under the premise that more experienced boards may be less prone to irrational pessimism when confronted with adverse events. We split the sample into high-tenure and low-tenure boards based on the median of the tenure distribution by industry-year-county. In untabulated tests, our main results are observed only among firms led by low-tenure boards, whereas they largely disappear for high-tenure boards. This pattern suggests that experience conditions how managers translate nearby disaster exposure into cost-adjustment decisions.

5.2. *Firm and industry characteristics*

Geographical diversification likely shapes how *NEIGHBOR* firms perceive and react to nearby disasters. Firms with limited geographic dispersion are more exposed to local risk and may therefore be more prone to irrational pessimism when a disaster occurs in close proximity. Accordingly, we expect salience-driven cost responses to be strongest among geographically concentrated firms. Consistent with this intuition, in untabulated tests, our main *NEIGHBOR* results are observed only for low-diversification firms, while they largely disappear for geographically diversified firms.

Industry characteristics may also shape firms' responses to nearby natural disasters. Manufacturing firms are more directly exposed to physical disaster risk due to their heavier reliance on tangible assets and complex supply chains (Dessaint and Matray 2017), which implies that their responses are more likely to reflect rational operational considerations. By contrast, non-manufacturing firms are less directly exposed to physical damage, making them more susceptible to salience-driven or irrational pessimism when disasters occur nearby. Consistent with this prediction, in untabulated tests, our main *NEIGHBOR* results hold only for non-manufacturing firms.

6. Conclusion

This study examines how managers respond to natural disasters through their cost management decisions. To examine our research question, we employ a sample of publicly listed US companies covering the period 1993–2019 and the asymmetric cost behaviour model proposed by Anderson et al. (2003). Furthermore, we measure natural disasters using FEMA data and differentiate between firms located in counties hit by natural disasters and those located in neighbouring areas.

We find no significant change in cost stickiness for firms located in directly affected regions, which may be explained by offsetting forces such as operational disruptions, abnormal demand conditions, and insurance payouts or government assistance. In contrast, our results provide robust evidence that neighbouring firms exhibit lower SG&A cost stickiness. Additional analyses suggest that this behaviour reflects irrational managerial pessimism rather than economic fundamentals, as these managers systematically underestimate subsequent sales, neighbouring counties are not more likely to experience future natural disasters, and these firms do not experience contemporaneous slower sales growth after nearby events. Overall, these findings are consistent with salience theory, which predicts that managers become more pessimistic after being exposed to salient negative events, even when their firms are not directly affected.

Our study has certain limitations. First, our analysis focuses on publicly listed U.S. firms, and the findings may not generalise to private firms or to institutional environments outside the US. Second, we rely on FEMA disaster declarations to identify natural disasters. While this approach allows us to focus on events that meet a regulatory threshold of materiality, we fully acknowledge that even within this definition, the economic magnitude of damage and operational disruptions can vary considerably across disasters and across firms. Relatedly, because we measure disaster exposure at the county level, not all firms located in a declared county are necessarily equally affected, as natural disasters are often highly localised phenomena. That said, our county-level approach remains more granular than the state- or country-level measures commonly used in prior research (e.g. Huang et al. 2018, Truong et al. 2020). Third, to determine whether firms are affected by a natural disaster, we follow prior literature and base our analysis on the county of their headquarters. However, firms may have the majority of their production in other counties, which could limit the power of our analysis. Finally, while we document systematic changes in cost behaviour following natural disasters, the precise mechanisms underlying these responses are inherently difficult to identify empirically. In particular, we cannot directly observe managerial beliefs, expectations, or internal decision-making processes, and therefore cannot conclusively disentangle behavioural channels from operational or strategic considerations.

Despite these limitations, our study provides initial empirical insights into how natural disasters influence fundamental corporate operating decisions, with important practical implications. Our findings suggest that managers may adopt overly conservative cost management strategies in response to nearby disasters, even when their firms are not directly affected, highlighting the importance of structured decision-making processes to mitigate behavioural biases. In addition, investors and analysts should be aware that changes in cost behaviour may not fully reflect underlying economic fundamentals. Finally, our results indicate that the economic effects of natural disasters may extend beyond directly affected regions, which may also be relevant for policymakers.

Using more granular firm-level data, future research could build on our findings to explore in greater depth how individual firms respond to natural disasters and which factors drive these responses. In this context, the role of insurance, for instance, represents a promising avenue for further investigation – one that our study was unable to address due to data limitations. As natural disasters are expected to increase in frequency and severity due to climate change, further research in this area is clearly warranted.

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No potential conflict of interest was reported by the author(s).

Data availability

All the data used are publicly available from the sources cited in the text.

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Appendix. Definition of variables

Name	Description
Change in COGS, SGA (*ΔlnCOGS*, *ΔlnSGA*)	Change in the natural logarithm of a firm's cost of goods sold (*COGS*) and selling general and administrative costs (*SGA*).
Change in Sales *(ΔlnSALES*)	Change in the natural logarithm of a firm's sales (*SALE*).
Decrease (*DEC*)	Indicator variable that equals 1 if sales (*SALE*) decrease from the previous year, and 0 otherwise.
HIT	Dummy variable which takes the value of 1 if the firm headquarters is located in a county hit by a natural disaster in the 12 months prior to the fiscal year-end (*DATADATE*), 0 otherwise.
NEIGHBOR	Dummy variable which takes the value of 1 if the firm headquarters is located in a county close to one hit by a natural disaster (and not in one directly affected) in the 12 months prior to the fiscal year-end (*DATADATE*), 0 otherwise.
Asset Intensity (*AI*)	Total assets (*AT*) divided by sales (*SALE*).
Employee Intensity (*EI*)	Number of employees (*EMP*) divided by sales (*SALE*).
Cash Flows (*CF*)	Cash flow, measured as cash flow from operating activities (*OANCF*) – common (*DVC*) and preferred dividend (*DVP*) payments scaled by total assets (*AT*).
Successive decrease (*SUC_DEC*)	Indicator variable that equals one if sales (*SALE*) in year *t-1* are less than those in year *t-2*, and zero otherwise.
Sales Guidance Optimism (SGO)	The difference between the sales guidance issued (SAL) after the first quarter and the corresponding realised sales (ACTUAL), scaled by total assets at the beginning of the year.

Notes: In parentheses, the COMPUSTAT North America code.