Facility Compliance and Natural Disaster Events: Evidence From the U.S. Clean Air Act

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With the increasing severity and frequency of natural disasters, we investigate the impact of such events on company environmental performance in the United States. This study analyzes the effect of natural disasters on facility compliance with the Clean Air Act throughout the sample period from 2013 to 2022. Our findings show that facilities located in disaster areas are associated with higher violation rates. By examining individual types of disasters separately, we find that the results are most pronounced for floods, fires, and severe storms. We suggest that regulators collectively evaluate the environmental policies and practices for companies in areas prone to natural disasters.

Keywords: facility compliance, natural disasters, The Clean Air Act

INTRODUCTION

Natural disasters have been on the rise in recent years in both magnitude and frequency. Impacted communities face a long road to recovery, dealing with numerous casualties and injuries and economic damage that may or may not be partially covered by insurance and government grants. Assessing tangible monetary losses is clearly needed to better assist policymakers. However, other hidden costs and expenses that impacted areas encounter in the aftermath of natural disasters have not been well explored in the literature.

In the current era of Environmental, Social, and Governance (ESG) considerations, many communities and businesses are taking environmental impact into account. We contribute to the literature by connecting the governance aspect to environmental performance. With the rising severity and frequency of natural disasters, we are motivated to examine company compliance with the environmental regulations of the United States Environmental Protection Agency (hereafter EPA) in the event of natural disasters. This unexplored topic is particularly important as the United Nations' disaster-monitoring systems report that the number of disasters worldwide has more than quadrupled to around 400 a year since the 1970s. The U.S. is among the top countries, along with China and India, that the greatest number of natural disasters has hit over the past two decades[1]. Our research intends to fill the existing knowledge gap regarding facility compliance with environmental regulations after a natural disaster.

In a natural disaster, facilities in the impacted areas may change their environmental compliance strategies and behaviors. A natural disaster creates layers of challenges for business operations after it strikes an area, which may negatively impact facility compliance with environmental regulations. The first challenge concerns physical damage to production machinery, factory buildings, and warehouses. Depending on the location and severity of the disaster, businesses may be adversely affected by road closures, port shutdowns, disruptions in transportation, large-scale power outages, disconnected water supplies, and the need for hazardous waste disposal for an extended duration.

In addition to the negative impacts from the tangibles mentioned above, a natural disaster may bring other challenges to underlying business operations, including supply chain disruptions in upstream and downstream logistics (Carvalho, Vasco, and Alireza Tahbaz-Salehi, 2021), negative migration to the region (Boustan, Kahn, Rhode, and Yanguas, 2020), loss of human capital (Gallagher, Billings, and Ricketts, 2023; Opper, Park, and Husted, 2023), and difficulty in retaining experienced staff. When businesses adjust their priorities during recovery, they may reallocate limited resources toward financial needs and budgeting, leading to diminished and inefficient production and operations. As a result, businesses may not have enough resources to prioritize compliance. Thus, we might expect an adverse effect on facility compliance after natural disasters.

We analyze the effect of natural disasters on facility environmental performance. Using natural disaster data declared by the Federal Emergency Management Agency (FEMA), we examine the impact of natural disaster events on facility compliance with the EPA's Clean Air Act (CAA) regulations throughout 2013–2022. Our findings show that facilities located in declared disaster areas are associated with higher violation rates. By investigating individual types of disasters separately, we find that the results are most pronounced in floods, fires, and severe storms.

The contribution of this study is multifaceted. First, to the best of our knowledge, our research is the first to examine the effects of natural disasters on firm environmental performance in the existing literature. This provides a better understanding of the impact of natural disasters in this unexplored area. Second, our results reveal the interplay between environmental performance and EPA enforcement in an uncontrolled natural disaster setting. Third, this study offers important policy implications. Regulators can collectively evaluate their established environmental policies and compliance practices with firms in areas prone to future natural disasters. Lastly, we provide insights that will benefit government agencies and advocacy organizations, such as FEMA, the International Red Cross, and CERES, in implementing cross-organizational partnerships in the future.

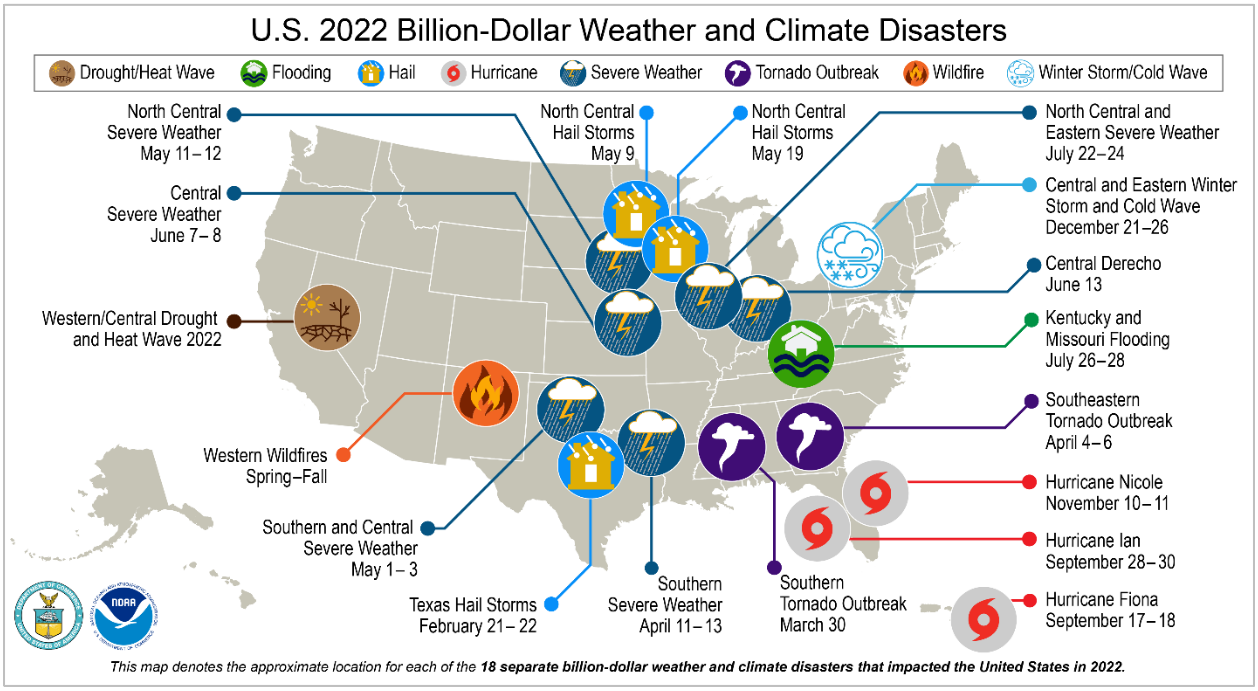
The rest of the paper is organized as follows: Section 2 provides an overview of natural disaster events and literature reviews. Section 3 presents the data and research methods, followed by the empirical results and analyses in Section 4. Finally, we conclude the study and provide suggestions in Section 5.

OVERVIEW OF NATURAL DISASTER EVENTS AND RELATED LITERATURE REVIEWS

Impact of Natural Disaster Events

A natural disaster is the negative impact following the actual occurrence of a natural hazard event that significantly harms a community or society. This study specifically considers weather- and climate-related natural disaster events[2]. The U.S. is among the top countries experiencing the greatest number of natural disasters over decades (*The Economist*, 2017). As extreme weather events continue to loom and the threat of climate change intensifies, the harmful impact is expected to escalate. The National Centers for Environmental Information (NCEI) of the National Oceanic and Atmospheric Administration (NOAA) has released its final update for the billion-dollar disaster report for 2022 (NOAA, 2022). In 2022, the U.S. experienced 18 billion-dollar disasters, resulting in at least $165 billion in losses. It was the third costliest year for billion-dollar disasters in U.S. history since 2000, following 2017 (an active Atlantic hurricane season with consecutive hurricanes Harvey, Irma, and Maria) and 2005 (caused by Hurricane Katrina). **Figure 1** shows the various types of natural disasters in the U.S. in 2022.

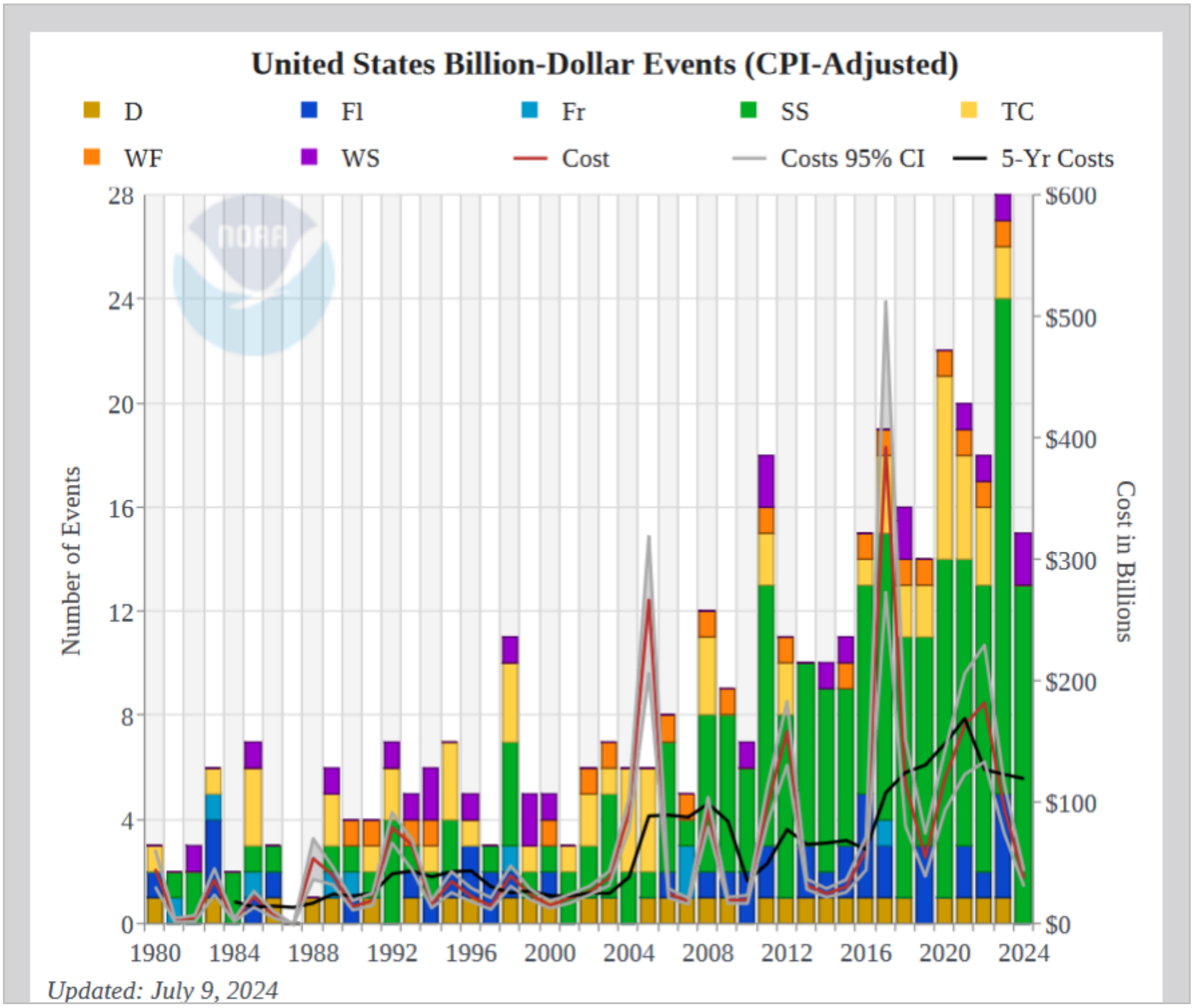
FIGURE 1
KEY WEATHER- AND CLIMATE-RELATED NATURAL DISASTER EVENTS IN THE U. S. IN 2022



Source: https://www.climate.gov/media/14987, and accessed June 5, 2024

Figure 2 shows the historical trend of million-dollar natural disaster events in the U.S. As depicted in the figure, the frequency and damage costs of billion-dollar natural disasters have far exceeded reasonable expectations in recent years. During our study period from 2013 to 2022, there were 155 confirmed weather/climate billion-dollar disaster events, totaling more than $1.1 trillion in damage costs. These events included 9 droughts, 17 flooding events, 1 freeze event, 92 severe storms, 22 tropical cyclones, 8 wildfires, and 6 winter storms, according to statistics from NCEI (NOAA, 2024).

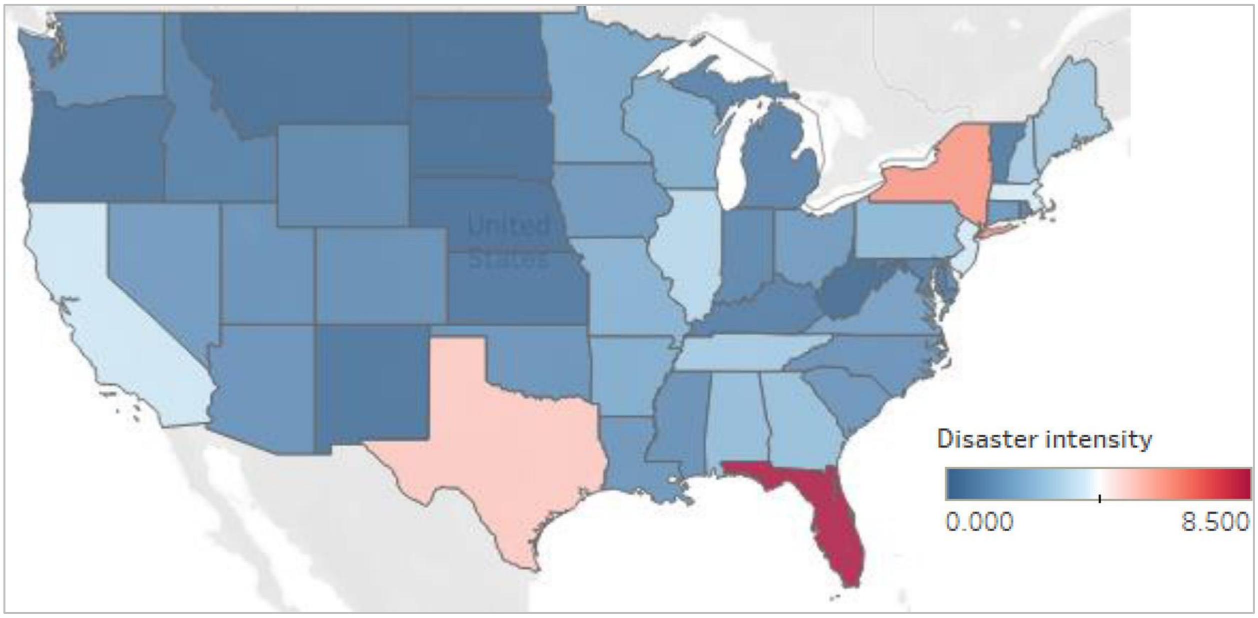
FIGURE 2
US BILLION-DOLLAR NATURAL DISASTER EVENTS AND THEIR DAMAGE AMOUNT



Source: NOAA 2024, accessed by https://www.ncei.noaa.gov/access/billions/.D refers to droughts, Fl refers to flooding, FR refers to freeze, SS refers to severe storms, TC refers to tropical cyclones, WF refers to wildfires, WS refers to winter storms.

We next review the geographical distribution of natural disaster frequency across the United States. **Figure 3** presents the intensity of natural disasters, measured by the average number of disasters, across the U.S. The three hardest-hit areas are southeastern Florida, northeastern New York, and Texas. Although the occurrence of natural disasters and the associated economic damage are uncontrollable and mostly unpredictable, we cannot underestimate the negative impacts these incidents have on communities and society.

FIGURE 3
THE GEOGRAPHICAL DISTRIBUTION OF NATURAL DISASTER INTENSITY, BY THE AVERAGE OF NUMBER OF DISASTERS, IN 2007-2018



Source: Aker, Cumming, and Ji, 2023, p. 4

Literature Reviews of the Impacts of Natural Disaster Events

The economic impacts of natural disasters have been well documented in the literature. Carvalho, Vasco, and Alireza Tahbaz-Salehi (2021) examined the effect of the 2011 earthquake in Japan and its aftermaths found a significant decline of 0.47 percentage point in Japan's real GDP growth in the year following the disaster. They also documented disruptions in upstream and downstream supply chains caused by disasters, affecting disaster-stricken firms' direct and indirect suppliers and customers. Using county-level data on the occurrence of natural disasters in the U.S., Barrot and Sauvagnat (2016) found that shocks to suppliers due to natural disasters impose substantial output losses on their direct customers and propagate to firms that share common customers with the disrupted firms. Boustan, Kahn, Rhode, and Yanguas (2020) argued that a natural disaster event might affect the local economy in several ways: reducing firm productivity by destroying productive capital or disrupting supply chains, creating unanticipated disamenities for consumers, and demolishing part of the inventory or reinvestment of housing stock.

Natural disasters also impose various impacts on the financial markets, which, in turn, alter firms' strategic behaviors. When a hurricane hits, investor uncertainty increases, resulting in abnormal volume, stock volatility, spreads, and illiquidity for impacted firms (Stamenov, 2022). Furthermore, Aker, Cumming, and Ji (2023) found that firms are more likely to engage in frequent and severe market manipulations due to sentiment and information asymmetry during disaster periods. In addition, the sentiment following various types of natural disasters is quite different (Jha, Liu, and Manela, 2021). As a result, firms impacted by disasters may reconsider their priorities when handling the recovery process.

The impacts of natural disasters are not limited to the economic and financial aspects discussed above. Both Opper, Park, and Husted (2023) and McDermott (2016) documented long-term adverse effects on human capital accumulation in communities after natural disasters. Opper, Park, and Husted (2023) found that natural disasters impact a region's human capital by reducing student learning, thus negatively affecting lifetime earnings. McDermott (2016) indicated that households impacted by disasters face reduced financial access, indirectly affecting student enrollment in human capital accumulation.

Literature Reviews of Facility Compliance With CAA Regulations

Company compliance with CAA regulations has been widely studied (Gray and Deily, 1996; Gray and Shimshack, 2011; Shimshack, 2014; Liu and Yang, 2020). For example, Gray and Deily (1996) found that increased enforcement actions lead to better compliance in the U.S. steel industry, resulting in less future enforcement. Deily and Gray (2007) found that being the target of EPA enforcement activities in the prior two years increases the probability of a plant complying by about 32%. Liu and Yang (2020) found similar targeting effects, where being classified as a high-priority violation effectively makes a facility an enforcement target, providing an extra incentive for the facility to return to compliance.

Nadeau (1997) investigated air emissions in the paper and pulp industry and found that monitoring activities reduce non-compliance duration. In addition, Keohane, Mansur, and Voynov (2009) showed that coal power plants reduce emissions by about 10% more when they are threatened by lawsuits due to violations. Overall, monitoring and enforcement actions by the EPA generate substantial deterrence effects, improving facility compliance and reducing future violations, regardless of the environmental regulations (Shimshack, 2014). Ultimately, better facility compliance reduces enforcement actions from regulators (Gray and Shimshack, 2011). More recently, Rijal and Khanna (2020) found that facilities in compliance increase their air emissions when a sister or affiliate facility belonging to the same parent company is in violation.

Several papers investigate the differential effects of enforcement on compliance (Deily and Gray, 2007; Alberini and Austin, 1999; Earnhart, 2009; Hanna and Oliva, 2010). Together, these studies suggest that a firm's response to enforcement efforts from regulators can vary due to several characteristics, such as firm size, ownership structure, permit conditions, and abatement costs.

As seen from the previous discussion, the impacts caused by natural disasters may lead to layers of difficulties for businesses. Firms may need to reallocate their limited resources to recovery activities from natural disasters. Thus, they may have to cut their budget for environmental compliance, resulting in difficulty balancing productivity and compliance requirements. As a result, maintaining compliance may be challenging for facilities in declared natural disaster areas. Given these challenges, we aim to investigate the relationship between facility compliance with environmental regulations and the effect of natural disasters.

DATA AND METHODOLOGY

Data

Our compliance and enforcement data came from the EPA's Enforcement and Compliance History Online (ECHO) database. We focused on manufacturing facilities that were subject to CAA regulations. To obtain a balanced panel dataset, we included only facilities that operated throughout the sample period, 2013–2022. For each facility in our sample, we obtained its annual violation status, the number of inspections, the number of enforcement actions, the penalty imposed, and whether a facility was considered to be in high priority violation (HPV).

We obtained natural disaster data from the Federal Emergency Management Agency (FEMA) of the Department of Homeland Security (DHS) in the USA, which maintains a database of natural disaster declarations. FEMA defines a natural disaster as any type of severe weather that poses a significant threat to human health and safety, property, critical infrastructure, and homeland security. This study specifically considers weather- and climate-related natural disaster events.

Natural disasters occur seasonally and without warning, subjecting the nation to frequent periods of insecurity, disruption, and economic loss. Certain types of natural disasters occurred only once within our sample period, leading to multicollinearity issues within our model. Therefore, we excluded such types. The natural disasters we consider are floods, fires, hurricanes, severe storms, and tornadoes. The natural disaster data were matched with facility information based on the county and the year of occurrence. For example, suppose a facility is located within a county where a natural disaster was declared during a specific year. In that case, we consider the facility to be in a natural disaster area during that year.

We also obtained county-level characteristics data from various sources, including the U.S. Census Bureau, the U.S. Bureau of Labor Statistics, and the U.S. Bureau of Economic Analysis. We collected two annual county-level economic variables: real annual income per capita and total employment in the manufacturing industry. We also included two demographic variables: population density and the percentage of the population with a high school diploma or above. We then matched the facilities to the demographic data based on their county and year. **Table 1** summarizes our data, including variable names, descriptions, and corresponding data sources.

TABLE 1
VARIABLE DESCRIPTIONS AND DATA SOURCES

Variable	Description	Data Source
Violation Rate	Percentage of time a facility is in violation in a given year	EPA/ECHO database
Natural Disaster	Dummy variable that takes a value of 1 if a facility is in a weather-and climate-related natural disaster area in a given year, and 0 otherwise	FEMA /Natural Disaster Declaration database
Inspection	Total number of inspections in a given year	EPA/ECHO database
Enforcement	Total number of enforcement actions in a given year	EPA/ECHO database
Penalty	Total amount of fines in a given year, in thousands of dollars	EPA/ECHO database
HPV	Dummy variable that takes a value of 1 if a facility is a high priority violator in a given year, and 0 otherwise	EPA/ECHO database
Income per capita	Annual income per capita at the county level, adjusted by CPI, in millions of dollars	US Census Bureau, US Bureau of Economic Analysis
Employment	Total employment in manufacturing facilities at the county level	US Bureau of Labor Statistics; US Bureau of Economic Analysis
Population Density	Number of persons per square mile at the county level	US Census Bureau; US Bureau of Labor Statistics; US Bureau of Economic Analysis
Education	Percentage of population with high school diploma and above at the county level	US Bureau of Economic Analysis

Table 2 shows the summary statistics of key variables. After matching the available data, we included 31,955 CAA-regulated facilities in our sample. We calculate the violation rate as the percentage of time that a facility is in violation of the regulation, which is the number of months a facility is in violation in a year divided by 12. On average, facilities are in violation 0.8% of the time. The next variable, ***natural disaster***, is our variable of interest, indicating whether a facility is in a declared natural disaster area within a given year. On average, about 7% of the facilities (about 2237 facilities) are in a natural disaster area in a given year.

The next three variables, ***inspections***, ***enforcement***, and ***penalty***, capture the annual monitoring and enforcement actions imposed on a facility. There are two types of enforcement actions: civil administrative actions and civil judicial actions. Civil administrative actions may include a notice of violation or an order for the facility to take action to return to compliance. Civil judicial actions are formal lawsuits against violating facilities. On average, a facility can expect almost one inspection per year. The average penalty imposed in a given year is $2,360. Note that not all violations result in monetary fines. About 22% of the facilities were fined at least once during our sample period, with the largest fine being as high as $10.15 million.

The next variable, ***HPV***, tracks whether a facility is considered to be in high-priority violation in a given year. According to the EPA's HPV policy, facilities with HPV status usually face more intense monitoring and enforcement actions, giving them more incentive to correct violations. In a given year, about 3% of facilities are in HPV status for at least one month.

The next group of variables is county-level characteristics. As discussed earlier, these include real annual income per capita, total employment in the manufacturing industry, population density, and the percentage of the population with a high school diploma or above.

TABLE 2
SUMMARY STATISTICS OF KEY VARIABLES

Variables	N	Mean	Standard Deviation	Min	Max
Natural Disaster					
Natural disaster dummy	319,550	7.00%	25.51%	0	1
Flood dummy	319,550	2.02%	14.07%	0	1
Fire dummy	319,550	0.47%	6.85%	0	1
Hurricanes dummy	319,550	2.85%	16.64%	0	1
Severe Storm dummy	319,550	1.28%	11.22%	0	1
Tornado Storm dummy	319,550	0.29%	5.33%	0	1
Facility Characteristics					
Violation Rate	319,550	0.82%	0.03%	0	100%
Inspection	319,550	0.82	1.94	0	93
Enforcement	319,550	0.06	0.37	0	32
Penalty	319,550	2.36	63.78	0	10,150
HPV	319,550	0.03	0.17	0	1
County Characteristics					
Income per capita	319,550	63.66	20.21	7.89	214.14
Employment	319,550	24,487.69	51,961.97	1	398,530
Population Density	319,550	1,780.41	7,175.59	0.04	73,111.13
Education	319,550	90.12	6.76	46.28	99.99

This table presents summary statistics of key variables related to facility and county-level characteristics used in the model. All facility characteristics variables account for facilities operating throughout the sample period of 2013 – 2022.

Methodology

To examine the effect of disaster on facility compliance, we adopt the following empirical model.

$$V_{ijt} = \alpha_0 + \sum_{l=1}^{2} \rho_n V_{ijt-l} + \beta I_{it-1} + \eta E_{it-1} + \gamma P_{it-2} + \theta H_{it-1} + \lambda D_{it-1} + \delta' C_{jt} + \varphi'^{Y_t} + u_i + \varepsilon_{ijt} \quad (1)$$

Here the dependent variable V_{ijt} is the percentage of time that facility i in county j is in violation of the regulatory requirements in year t.V_{ijt-l} is the lagged dependent variable, where $l = \{1,2\}$. $I_{it-1}, E_{it-1},$ and P_{ijt-2} denote the lagged monitoring and enforcement variables, inspection, enforcement, penalty, respectively. H_{it-1} is a dummy variable that takes a value of 1 if a facility is in HPV status in year *t-1*, and 0 otherwise. D_{it-1} is a dummy variable that takes a value of 1 if a facility is in the declared disaster area in year *t-1* and 0 otherwise. C_{jt} includes county economic and demographic characteristics. The year dummies and individual facility fixed effects are denoted by Y_t and u_i, respectively. The random error term is denoted by ε_{ijt}.

Our choice of lagged monitoring and enforcement variables is based on two major considerations. The first is the endogeneity issue that may arise when enforcement is included as an explanatory variable in the analysis of violations. Monitoring and enforcement actions imposed on a facility by the EPA may be based on its compliance status. Facilities with HPV status are especially likely to be inspected since they are considered high priorities. This gives rise to reverse causality and endogeneity, such that a facility's violation induces inspection and enforcement. If no actions are taken to control for endogeneity, a positive relationship may be observed between violation and inspection, where more inspections are correlated with more violations. Therefore, the monitoring and enforcement variables, $I_{it-1}, E_{it-1},$ and P_{ijt-2} are included in our model with 1–2 years lag to address the endogeneity issue. This method has been adopted in prior literature (Magat and Viscusi, 1990; Gray and Shimshack, 2011; Liu and Zhou, 2020). Second, it may take time for a violating facility to take actions to return to compliance, and thus, a facility's violation status may persist over time. Therefore, it is more reasonable to expect that monitoring and enforcement actions taken in the previous year will affect facility compliance in the current year.

A facility's violation may take months or even years to correct, but its compliance status could be correlated over time. Therefore, we adopt a dynamic panel data approach and include one-year and two-year lags of compliance status as control variables. The characteristics that influence a facility's compliance may be captured by past compliance behavior. Thus, including past compliance could potentially control for such implicit characteristics. When lagged compliance is included in the model as a control variable, traditional Ordinary Least Squares (OLS) estimators become inconsistent. We, therefore, adopt the Arellano and Bond (1991) approach to estimate the dynamic panel data model. The Arellano and Bond estimator is a consistent Generalized Method of Moments (GMM) estimator for situations where lagged dependent variables are included as explanatory variables. The choice of one- and two-year lags is determined based on the results of the Autocorrelation Test shown in the next section.

EMPIRICAL RESULTS

Natural Disaster and Compliance

Table 3 reports the empirical results. Our main interest is to investigate the effect of natural disasters on facility compliance. We first examine this effect by aggregating different types of natural disasters and summarizing it with one dummy variable representing whether a facility is located in a natural disaster area. Model (1) in **Panel A** shows the regression results. The coefficient for the disaster dummy is positive and significant. This suggests that when a facility is in a disaster area in the previous year, its compliance in the current year deteriorates, as indicated by an increased violation rate. The regression coefficient shows an increase of 0.15% in the violation rate in a given year.

TABLE 3
EFFECT OF NATURAL DISASTERS ON FACILITY NONCOMPLIANCE: ARELLANO AND BOND (1991) ESTIMATOR MODEL

Panel A: Effect of natural disasters on facility violations: combined natural disaster events

	(1) Facility Violation Rate
Lagged disaster dummy	0.15135***
	(0.03226)
Lagged violation rate	0.20014***
	(0.01975)
Lagged (lag 2-year) violation rate	0.10629***
	(0.01172)
Lagged inspection	-0.36737***
	(0.02418)
Lagged enforcement	-0.64013***
	(0.12922)
Lagged (lag 2-year) penalty	-0.00081***
	(0.00030)
Lagged HPV dummy	-3.45909***
	(0.15137)
Income per capita	-0.00263
	(0.00295)
Manufacturing employment	-0.00001
	(0.00000)
Population Density	-0.00018***
	(0.00006)
Education	-0.03442***
	(0.01261)
Facility fixed effects	YES
Year fixed effects	YES
Observations	223,685
Arellano–Bondautocorrelation testAR(2) (p-value)	0.5164

This table reports the regression results. Facility violation is measured by the percentage of time a facility is in violation in a given year t. The key variable of interest is *Lagged Disaster Dummy*, which equals 1 if the facility was in the natural disaster area in the year *t-1*, and 0 otherwise. The regression includes controls for facility fixed effects and year fixed effects. Robust standard errors are reported in parentheses below each coefficient estimate. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Next, we present the results for each disaster type separately in **Panel B**. The results show a similar impact of experiencing a natural disaster on facility compliance. Each type of natural disaster has a positive coefficient, which is significant in Models (2), (3), and (5), corresponding to flood, fire, and severe storm, respectively. Among the models with significant coefficients, the magnitude of the effects differs across the respective types of natural disasters. Severe storm events (Model 5) have the most pronounced effect on facility compliance, with facilities located in severe storm disaster areas in the previous year showing a 0.3% increase in the violation rate in the current year. Fire and flood show relatively similar effects, with a 0.20% increase in the violation rate for facilities located in fire disaster areas in the previous year, and a 0.16% increase for facilities located in flood disaster areas in the previous year.

Panel B: Effect of natural disasters on facility violations: by individual types of natural disasters

	(2) Facility Violation	(3) Facility Violation	(4) Facility Violation	(5) Facility Violation	(6) Facility Violation
Lagged **flood** dummy	0.15770**				
	(0.06979)				
Lagged **fire** dummy		0.19471**			
		(0.10902)			
Lagged **hurricanes** dummy			0.06225		
			(0.04809)		
Lagged **severe storm** dummy				0.30571***	
				(0.06982)	
Lagged **tornado storm** dummy					0.03925
					(0.12957)
Lagged violation rate	0.20025***	0.20044***	0.20027***	0.20031***	0.20034***
	(0.01974)	(0.01974)	(0.01974)	(0.01975)	(0.01974)
Lagged (lag 2-year) violation rate	0.10641***	0.10649***	0.10637***	0.10634***	0.10642***
	(0.01171)	(0.01171)	(0.01171)	(0.01172)	(0.01171)
Lagged inspection	-0.36754***	-0.36756***	-0.36753***	-0.36753***	-0.36759***
	(0.02418)	(0.02419)	(0.02418)	(0.02418)	(0.02419)
Lagged enforcement	-0.64010***	-0.64077***	-0.64015***	-0.63998***	-0.64025***
	(0.12923)	(0.12925)	(0.12923)	(0.12922)	(0.12924)
Lagged (lag 2-year) penalty	-0.00081***	-0.00081***	-0.00081***	-0.00081***	-0.00081***
	(0.00030)	(0.00030)	(0.00030)	(0.00030)	(0.00030)
Lagged HPV dummy	-3.45987***	-3.46008***	-3.45959***	-3.45959***	-3.45988***
	(0.15138)	(0.15140)	(0.15138)	(0.15139)	(0.15139)
Income per capita	-0.00203	-0.00182	-0.00235	-0.00210	-0.00203
	(0.00295)	(0.00295)	(0.00295)	(0.00295)	(0.00295)
Manufacturing employment	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Population Density	-0.00021***	-0.00020***	-0.00020***	-0.00021***	-0.00021***
	(0.00006)	(0.00006)	(0.00006)	(0.00006)	(0.00006)
Education	-0.03423***	-0.03488***	-0.03406***	-0.03442***	-0.03425***
	(0.01262)	(0.01261)	(0.01262)	(0.01261)	(0.01262)
Facility fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	223,685	223,685	223,685	223,685	223,685
Arellano–Bondautocorrelation testAR(2) (p-value)	0.5171	0.52	0.5246	0.525	0.5238

This table reports the regression results. Facility violation is measured by the percentage of time a facility is in violation in a given year *t*. The key variable of interest is *Lagged **Disaster** Dummy*, which equals 1 if the facility was in a specific type of natural disaster area, including **flood, fire, hurricane, severe storm, and tornado storm**, in the year *t-1*, and 0 otherwise. The regression includes controls for facility fixed effects and year fixed effects. Robust standard errors are reported in parentheses below each coefficient estimate. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

The consistent positive effects of natural disaster events on facility violations suggest that when a facility encounters unexpected natural disasters, it may subsequently face difficulties in complying with environmental regulations. Natural disasters can lead to damage to factory buildings, repair needs for production equipment, road closures, disruptions in transportation, and power outages, as well as negative impacts such as loss of human capital and reallocation of financial resources. Consequently, facilities located in disaster-affected areas, especially those in severely disrupted regions, are expected to struggle with maintaining compliance. The positive association between natural disaster events and facility non-compliance is thus clearly justified.

Monitoring and Enforcement Measures, HPV and Compliance

The general monitoring and enforcement measure we consider in the regression include the annual number of inspections and enforcement actions, the annual penalty imposed, and the classification of HPV. As expected, all measures show significant deterrent effects against facility violations in all six models. The more frequently inspections and enforcement actions are taken on a facility in the previous year, the lower the subsequent violation rate. Each inspection or enforcement action in the previous year leads to a decrease in the violation rate by 0.37% and 0.64%, respectively, in the current year.

Interestingly, fines imposed on a facility significantly impact the improvement of the facility's violation rate with a 2-year lag. One possible explanation for this 2-year lag is that fines are usually imposed for serious violations, which in turn require a facility significant time and effort to adjust and meet compliance requirements. Additionally, a facility classified as HPV in the previous year has a significant and negative effect on the violation rate. This is expected because facilities labeled as HPV experience the highest level of scrutiny and oversight from the EPA. They face a series of enforcement actions and continuous monitoring until they restore compliance. On average, being classified with HPV status in the previous year reduces the violation rate in the current year by 3.5% for a given facility.

Other Control Variables

County characteristics also play a role in determining a facility's compliance behavior, although the effect is very limited. Facilities located in counties with a higher percentage of the population holding a high school diploma or higher tend to have a lower violation rate. Additionally, facilities in counties with higher population density also tend to have a lower violation rate. Areas with higher education levels or population density are typically urban. The negative and significant coefficients found for education and population density may suggest that facilities in such areas either comply better with regulators due to community pressure or face more stringent enforcement. The other two variables, income per capita and manufacturing employment, do not have any statistically significant effects.

All lagged dependent variables are statistically significant, as shown in **Table 3**. This indicates that a facility's non-compliance rate depends on its compliance history, implying dynamic adjustments in its compliance behavior. Therefore, it is important to include lagged dependent variables to control for preexisting conditions and to mitigate the endogeneity problem arising from possible unobservable factors influencing compliance behavior

Finally, as shown in **Table 3**, the Arellano-Bond test for autocorrelation for all models fails to reject the series correlation in the first- differenced errors at order 2, supporting the choice of two-year lags of the dependent variable used in the model.

CONCLUSION

This study investigates the effect of natural disasters on environmental performance. We estimate dynamic panel data models using data from 31,955 major manufacturing facilities in the U.S. from 2013 to 2022. Our results reveal a negative association between natural disasters and facility compliance with CAA regulations. A facility located in a declared natural disaster area in the previous year is followed by a higher violation rate in the current year. We also explore how each type of disaster affects facility compliance. Interestingly, the association between disasters and facility compliance varies significantly among different types of natural disasters. Severe storm events show the greatest impact, with the highest magnitude of effect, followed by fire and flood events. Additionally, we find significant deterrent effects from general monitoring and enforcement measures, including inspections, enforcement actions, imposed penalties, and the classification of HPV.

The key message to regulators is that they should collectively evaluate their established environmental policies and compliance practices for firms in areas prone to natural disasters. Since natural disasters can adversely impact a firm's compliance decisions, which in turn can negatively affect the environment, firms must have better risk management strategies to cope with uncontrollable natural disaster events, particularly in disaster-prone areas. Precautions should be taken based on location and season to better prepare for future natural disasters. Additionally, policymakers should consider the negative effects of natural disasters on firm compliance when evaluating the overall impacts of such events.

ENDNOTES

1. Please refer to the report in The Economist: weather-related disasters are increasing (2017/8/29), which can be accessed via https://www.economist.com/graphic-detail/2017/08/29/weather-related-disasters-are-increasing.
2. Our research design deliberately excludes the COVID-19 global pandemic from the categories of declared natural disasters by FEMA in our data. We do this to avoid research bias in our empirical study, as a significant majority of the U.S. was declared affected by the COVID-19 disaster according to FEMA data.

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