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Jacob Kim-Sherman | Lee Seltzer

FEDERAL RESERVE BANK of NEW YORK

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Abstract

In contrast with findings in climate science, economists often treat losses from natural disasters as statistically independent of one another. To better incorporate scientific insights into economic research, we introduce a methodology to identify spatial and temporal clusters in datasets on losses from natural disasters. We find that expected damage increases non-linearly with relative cluster size. Additionally, county-level damage is correlated with the damage experienced by other counties in the same cluster. Our findings suggest that accounting for clustering allows for a more complete understanding of the economic consequences of natural disasters.

JEL classification: Q50, Q54
Key words: natural disasters, clustering

Kim-Sherman, Seltzer: Federal Reserve Bank of New York (emails: jacob.kim-sherman@ny.frb.org, lee.seltzer@ny.frb.org). The authors thank Hyeyoon Jung, Viral Acharya, Julian Di Giovanni, Matteo Crosignani, Martin Hiti, and Jose-Luis Cruz for useful comments and discussion.

In September 2024, Hurricane Helene struck the United States, with Federal Emergency Management Agency (FEMA) disaster declarations in five different states (Alabama, Florida, Georgia, North Carolina, and South Carolina). The disaster was estimated to cost \$47.5 billion in damage by CoreLogic. Mere weeks later, Hurricane Milton also hit Florida.[1] The wide-reaching footprint of Hurricane Helene beckons the question of whether Florida counties were affected worse by Helene since their neighboring counties were also affected by Helene. Additionally, it is possible that Florida counties may have been more adversely affected by Hurricane Milton, since Helene had occurred in the recent past. This paper introduces a methodology to account for *clustering* in natural disaster losses, which can be used to address such questions.

In previous work, most economic research on natural disasters involved using county-by-month level data to run panel regressions of different economic outcomes on disaster damages.[2] The regressions often include county and time fixed effects, clustering standard errors at the county-level, which requires assuming the error terms are uncorrelated across counties. At the same time, the climate science literature finds consistent evidence of clustering in natural disaster occurrences, where disasters tend to be concentrated either in certain regions or in short windows of time.[3] In this sense, clustering of disaster damages could be a challenge to this assumption of uncorrelated error terms. This paper integrates the concept of natural disaster clustering to the economics literature.

There are numerous reasons why clustering could have important implications for economic research. For example, if neighboring counties use the same resources to aid in recovery, these resources may be strained if all neighboring counties are affected by contem-

[1] CNN Business: As Hurricane Milton threatens the US, Helene could cost property owners more than \$47 billion.

[2] See, for example, Gallagher and Hartley (2017); Bleemer and van der Klaauw (2019); Billings et al. (2022); Gallagher et al. (2023); Kruttli et al. (2023); Correa et al. (2022); Blickle et al. (2021); Sastry (2021); Blickle and Santos (2022); Issler et al. (2021); Sastry et al. (2023); Deryugina (2017); Acharya et al. (2022); Tran et al. (2020); Bakkensen and Barrage (2018)).

[3] See, for example, Wheater et al. (2005); Li et al. (2016); Fu et al. (2023); Merz et al. (2021); Leonard et al. (2014); Zscheischler et al. (2018, 2020); Woodruff et al. (2013); Marsooli et al. (2019); Sarhadi et al. (2018)).

poraneous disasters. Additionally, counties may be less prepared for a disaster in the wake of another recent disaster. To allow researchers to consider these effects, this paper develops algorithmic approaches to identify spatial clusters (i.e., clusters across counties), temporal clusters (i.e., clusters across time), and spatiotemporal clusters (i.e., clusters across counties and time). To understand the implications of accounting for natural disaster clustering, we compare data on natural disaster damages aggregated to the cluster-level to data on natural disaster damages aggregated to the county-level.

The analyses reveal two key facts about clusters in natural disaster losses. First, we find a positive relationship between the relative size of a disaster cluster (measured by the number of counties contained in the cluster) and the amount of damage, and this trend is nonlinear. In particular, the average logged damage for all clusters in the 60th percentile and below is about 10 ($22 million). This is because there is little variation in cluster size at this point in the distribution, with the median cluster having a size of one county. However, at around the 60th percentile of cluster size, there is a sharp increase in disaster damages, and logged damages for the 95th percentile bin reaches about 15 logged damages ($3.3 billion). This suggests that an increase in relative size predicts a sharp increase in the expected level of damage, especially among very large clusters. Similarly, the distribution of the natural log of damages is more positive when examining cluster-level damages than county-level damages. At the same time, certain hazard types appear more severe when using a clustered approach than when using county-by-month level data.

We also find that county-level damages tend to be larger when the county is part of a cluster that experiences more damage. In particular, a county typically experiences about 0.25% more disaster damage if all the other counties in the same disaster cluster experience an additional 1% of damage. While not causal, this result could be consistent with counties facing greater damages from disasters when their neighbors face the same disasters due to strained resources. We also find these results are especially acute for certain hazard types, such as droughts, floods, hurricanes and wildfires.

To reiterate, this paper introduces a methodology to incorporate clustering of natural disasters into empirical economic research. We provide an approach to identify natural disaster clusters. We show that incorporating clustering into analyses increases the severity of the most severe natural disasters, as well as the severity of hazard types that tend to occur in large clusters. We also confirm that county-level disaster damages are higher when the rest of the cluster also experiences higher damages. These findings indicate that clustering could be important for assessing economic outcomes following disasters.

In the first section, we describe the data sources used and define the clustering methodology. In the second section, we examine data on cluster-level damages in comparison to data on county-level damages, and test how county-level damages are correlated to damage experienced by other counties in the same cluster. In the third and final section, we conclude.

1 Data and Methodology

1.1 Data

The primary data set used in our analysis is the Spatial Hazard Events and Losses Database for the United States (SHELDUS). SHELDUS provides information on the incidence of natural disasters at the county-by-hazard type-by-month level from 2000 until 2020 across 3,249 distinct counties in the United States.[4] While we focus on SHELDUS as it is the most widely used data set on natural disasters in economic research, this methodology could be easily adapted to other data sets on natural disaster losses.

These data include the type of natural disaster, categorized into 18 distinct hazard categories, as well as damages (divided into property and crop damages), fatalities, and injuries associated with the disaster. For control variables, we use Quarterly Census of Employment and Wages (QCEW) county-level dataset from the Bureau of Labor Statistics on wages,

[4]While SHELDUS also provides data at the natural disaster level, we use the county-by-disaster-type-by-month panel as it is the format most commonly used by researchers.

annual county-level datasets on population from the Census Bureau's American Community Survey (ACS) and county GDP from the Bureau of Economic Analysis for the period between 2000 and 2020.

1.2 Methodology

Most research designs that rely on a county-by-time level panel require assuming that the error terms are uncorrelated across county and time.[5] However, the climate science literature presents several important challenges to such an assumption.[6] Some counties may be unconditionally more likely to experience certain types of disasters. For instance, Florida counties experience more hurricanes than average, and California counties experience more wildfires than average. Additionally, if a county's neighbor experiences a disaster, this may raise the probability that the county itself experiences a disaster at the same time. If both counties are hit at the same time, this would likely strain the economic resources of each individual county more. The climate science literature also suggests that if a disaster lasts longer, this could exacerbate adverse economic consequences of the disaster. These challenges to the standard assumptions motivate developing a methodology to algorithmically identify common patterns of natural disasters, so that we can properly account for the correlation between disasters across space and time. We thus propose the following approaches for identifying common patterns of disasters in county-time level data.

1.2.1 Spatial Clustering

Consider a given county i in a given period t. We can define the following function $H(c_t^i)$ as outputting the set of hazards $H_t^i = \{h_m, ..., h_n\}$ where h_m denotes a hazard experienced by county i in time t. For example, the event experienced by Harris County, Texas in August 2017 (when Hurricane Harvey took place) can be described as $H(c_{2017m8}^{\text{Harris, TX}}) = \{$hurricane,

[5] A detailed literature review on natural disasters in economics is provided in Internet Appendix IA.A.

[6] A detailed literature review on natural disasters in climate science is provided in Internet Appendix IA.B.

flooding, tornado, thunderstorm}. Trivially, if c_t^i is not experiencing any hazards, this set would be the empty set.

We identify two counties (i, j) as having a *proximate common climate pattern* in time t if the counties, i and j, are geographically contiguous and they have at least one common hazard:

$$\begin{aligned} PCCP(i,j) =& 1 \text{ if counties i and j are adjacent and} \\ & H_t^i \cap H_t^j \neq \emptyset. \end{aligned}$$

where H_t^i and H_t^j are defined as above. Considering the example of Harris County, TX, in August 2017, in that same month neighboring Montgomery County, TX, experienced hurricane, wind, and flooding. Since Harris and Montgomery are adjacent, and $H_{2017m8}^{\text{Harris, TX}} \cap H_{2017m8}^{\text{Montgomery, TX}} = \{\text{hurricane, flooding}\} \neq \emptyset$, we would say that $PCCP$(Harris, TX; Montgomery, TX) = 1.

We define two counties (c^i, c^j) as sharing a *common climate pattern* if there is a "path," with distance n counties, from county i to county j where the intermediate counties are (pairwise) proximate common:

$$\begin{aligned} CCP(c^i, c^j) =& 1 \text{ if } \exists \text{ a set of counties, } \{k_1, \cdots, k_n\} \text{ such that} \\ & PCCP(c^i, k_1) = 1 \text{ and} \\ & PCCP(k_1, k_2) = 1 \text{ and} \\ & \cdots \\ & PCCP(k_n, c^j) = 1. \end{aligned}$$

A *spatial cluster* is defined as the largest possible set of counties in time t that corresponds to a common climate pattern. Looking at Figure 1, we can see the entire spatial cluster associated with Harris County, Texas in August 2017 (i.e., the spatial cluster associated with Hurricane Harvey), following this inductive process until no more proximate common climate patterns can be identified.

1.2.2 Temporal and Spatiotemporal Clustering

Much of the conceptual framework developed for identifying spatial clusters can be easily mapped to temporal clustering. We can identify a given county as having a *temporally persistent climate pattern* if it experiences the same climate hazard in at least two consecutive time periods:

$$TPCP(i,t) = 1 \text{ if } H_t^i \cap H_{t+1}^i. \neq \emptyset$$

This concept can be applied to combine spatial clusters in two consecutive time periods if at least one county experiences a temporally persistent climate pattern in both clusters. When this link can be established, the most expansive possible set of all of the counties experiencing proximate common and temporally persistent climate patterns is defined as a *spatiotemporal cluster*. We provide an extension of the Hurricane Harvey example to a spatiotemporal cluster in Internet Appendix IA.C. Note that the results in the main text will focus on spatial clusters, although the Internet Appendix contains analogous results for spatiotemporal clusters.

This approach is readily implementable in any statistical software such as Stata, Python, R, or Matlab. When executing the clustering algorithm, we classify the 161,664 county-months in which a hazard loss occurs to 37,296 spatial clusters and 28,495 spatiotemporal clusters.

1.3 Summary Statistics

Summary statistics on disasters at the using data at the cluster-level and at the county-level are displayed in Table 1. Data on the cluster-size, total damages, property damages, crop damages, injuries and fatalities are provided. The size of the average cluster is about 4 counties.

The average cluster's total damage is \$17.5 million. On the other hand, the median total damage is only \$23,600, indicating that the distribution is positively skewed.[7] The total damage numbers include both property and crop damages, although property damages contribute to 90% of the total damage. This could lead to analyses using SHELDUS data understating hazard types that result in relatively more crop damage than property damage, such as heat. The table also includes the distributions of injuries and fatalities, which also show larger average values using clustered approaches. All results in the main text are based on total damages, although results for specific damage types, injuries and fatalities are included in Internet Appendix IA.C.[8]

This section included a description of our new approach to identify clusters of natural disasters using data on natural disaster damages. In the next section, we will explore cluster-level disaster damages, to better understand how the choice of whether to examine disasters using county-level data or cluster-level data could impact the conclusions of researchers.

2 Comparing Cluster- and County-Level Damages

In the previous section, we described the clustering methodology we developed for this analysis, and introduced summary statistics on the clustered data. In this section, we will compare the cluster-level data on natural disaster damages with the county-level data on natural disaster damages. We will also examine whether counties tend to experience greater disaster damage when they are part of clusters that experience more severe disasters.

[7] These summary statistics include events in SHELDUS with zero damage recorded, although they look similar when excluding the zero-damage events.

[8] Note that by construction, the cluster-level distribution of damages will have more extreme values than the county-level distribution due to the effect of scaling. For this reason, all analysis in the paper making comparisons between counties and clusters will use the natural log of damage, to reduce the effects of outliers. We also include results examining the log of damages, scaled by the respective sample medians for counties and clusters, as well as by the respective hazard-specific medians for counties and clusters, in Internet Appendix IA.C.

2.1 Exploring disaster-level distributions

To visualize the distributions of damage according to the approach used, panel (a) of Figure 2 displays the histogram showing the distribution of logged damages measured at the county-level, overlaid with the distribution of logged damages at the cluster-level. The right tail of the cluster-level distribution has substantially more mass than the county-level distribution.[9] Internet Appendix IA.C displays a similar histogram with spatiotemporal clusters, as well as for crop damage and property damage. All appear similar to the result shown in the main text.

The histograms show that the clusters with the most damage are more extreme than the counties with the most damage. One potential explanation for this could be that disasters that cover larger areas tend to create more damage, and examining natural disasters in the form of a cluster allows you to observe this effect. To directly study whether disasters affecting more counties yield more damage, we study heterogeneity in cluster damages according to the cluster's size. Specifically, we sort clusters into percentile bins according to the number of counties contained in each cluster. Then, within each cluster, we calculate the average logged-damage. The results are displayed in panel (b) of Figure 2. There is little variation in disaster damage according to cluster size up until the 60th percentile, averaging about \$22 million. This is primarily because all clusters up until this point only have one county. However, disaster damage increases non-linearly at this point, eventually reaching average damage of \$3.3 billion at the 95th percentile. This highlights both that the cluster-level distribution of disaster damages includes some disasters with very large amounts of damage, and that larger clusters tend to have more disaster damage.

It is also possible that certain hazard types appear less severe using county-level data than cluster-level data. To assess this possibility, we regress logged damages on hazard type indicators. Specifically, we study droughts, extreme heat, wildfire, flooding and hurricanes.

[9] Two-sample Smirnov (1939) equality of distribution tests confirm that these two distributions are statistically different at the 1% level.

The results are displayed in Table 2. The constant of this regression can be interpreted as the average logged damages for all hazard types except the one explored using the hazard type indicator, after controlling for observables. The coefficient on the hazard type indicator is the marginal effect of additional damage for the hazard type of interest. For all hazard types explored, the marginal effect of each hazard type occurring is larger when using cluster-level data than when using county-level data.[10]

In this subsection, we showed that there exist important differences between the distributions of county-level data and cluster-level data. In particular, cluster-level data exhibits greater positive skewness than county-level data, and larger clusters tend to have greater disaster damage. We also find some evidence that some disaster types appear more severe using cluster-level data than county-level data. In the next subsection, we will study whether counties that are part of larger clusters tend to experience greater disaster damage. We will do this by testing whether county-level disaster damage varies according to disaster damage experienced by other counties located in the same cluster.

2.2 Relationship Between County-Damage and Cluster-Damage

Distributions using cluster-level data appear more skewed than when using county-level data, and climate events affecting more counties tend to yield higher damages. One potential explanation for this is that there could be "network effects" of disaster damage. In particular, it is possible that if a given county experiences a disaster at the same time that nearby counties face disasters, this could lead to higher disaster damages. This could be due to strained resources to mitigate the damages, or greater degradation of shared infrastructure between the counties. It is also possible that these network effects may be especially problematic for certain disaster types. To test these hypotheses, we implement the following regression:

[10] Internet Appendix IA.C shows results using injuries, fatalities, property damages and crop damages as outcome variables.

$$log(Damage_{c,t}) = \beta_1 \mathbb{1}_{c,t}[\text{Hazard=j}] \times log(Damage^{-c}_{i,t}) + \beta_2 \mathbb{1}_{c,t}[\text{Hazard=j}] + \beta_3 log(Damage^{-c}_{i,t}) + \Gamma X_{c,t} + \epsilon_{c,t}, \tag{1}$$

where $log(Damage_{c,t})$ is the log of damage of county c, at time t, $log(Damage^{-c}_{i,t})$ is the log of damage of cluster i (excluding damage for county c) at time t, and $\mathbb{1}_c[\text{Hazard=j}]$ are indicator variables equal to one if hazard type j occurs in county c at time t. $X_{c,t}$ are county-by-time controls. Specifically, to control for whether larger, or more populated areas, are more likely to experience severe disaster damage, we control for county GDP, population and wages. If larger clusters tend to experience more damage, we expect the that $\beta_3 > 0$. Additionally, if clustering makes certain hazard types look more severe, then we expect that $\beta_1 > 0$.

Results for these regressions are shown in Table 3. In all specifications, the estimate for β_3 is equal to about 0.25, meaning for that a 1% change in cluster-level damage is associated with a 0.25% increase in county-level damage. Moreover, for all hazard types except for heat, the estimate for β_1 is positive and statistically significant, meaning that these hazard types appear more severe when clustering is accounted for. One concern is that these results could be due to county-level characteristics or time trends. To this end, this table also includes results with county and time fixed effects, which yield the same conclusions.[11] Overall, these results are consistent with a tendency for counties to experience greater disaster damage when the rest of their cluster also experiences disaster damage, and with some hazard types appearing more severe when incorporating clustering into an analysis.

In this subsection, we learned that some hazard types look much more severe when using a clustered approach than a county-level approach. This could indicate that researchers

[11] Internet Appendix IA.C includes results using property damages, crop damages, injuries and fatalities as outcome variables, as well as a version of the test controlling for cluster-level observables in addition to county-level observables.

have underestimated the threat posed by these disasters by focusing on county-by-month level data.

3 Conclusion

It is clear that the temporal duration and the spatial footprint of natural disasters influence the intensity of damages they incur, and that damages from natural disasters tend to be spatially and temporally clustered. In this paper, we provide a tool for researchers to use to account for the correlated damages from natural disasters across counties and time. We find that accounting for clustering results in a more positively skewed distribution than when using county-level data. We also find that disaster damages in a particular county tend to be larger when the neighboring counties in its cluster are experiencing greater disaster damage.

As a note of caution, because neighboring counties may have correlated economic fundamentals, accounting for clustering presents a challenge when examining the economic impact of natural disasters. Nevertheless, this analysis provides researchers with a useful tool to further study how natural disaster clustering can affect economic outcomes following disasters.

Our analyses show that clustering is an important feature of how natural disaster losses accrue, and this may have important economic consequences. The tendency of natural disaster damages to cluster may induce correlated economic outcomes in counties hit by the same disaster cluster, an unexplored source of economic risk. Clustering could also hinder the process of recovering from natural disasters if shared resources within a relevant time frame or region are limited. Additionally, the correlated incidence of natural disaster damages across space and time could present challenges in insuring against natural disasters, leading to financial stability risks. These conjectures demonstrate the broad economic relevance of natural disaster clustering, and suggest that failing to take clustering into account may leave policy makers blind to an important source of risks.

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Figures

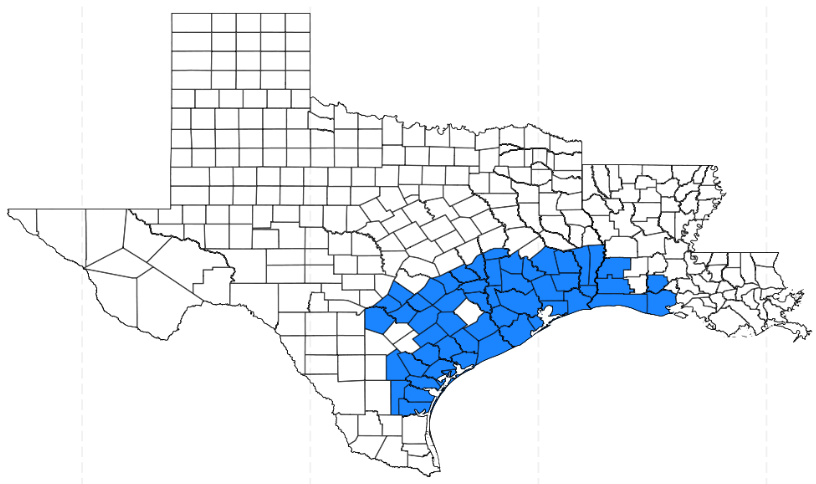
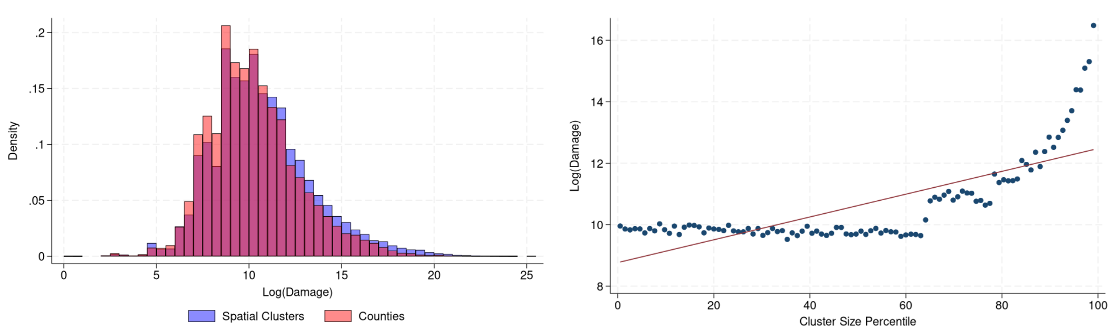


Figure 1: Spatial Cluster Containing Harris County, August 2017

This figure illustrates the entire set of counties that are included in the Harris County August 2017 spatial cluster as obtained in the procedure outlined in subsubsection 1.2.1.

Figure 2: Distributions of Damage Across Clusters

(a) Damage Histogram (b) Size vs Log(Damage)



Notes: This figure displays information on the distribution of damages across clusters. Panel (a) shows the distribution of the log of total damages defined at the cluster-level, alongside the distribution of the log of total damages defined at the county-level. Panel (b) shows the expected log damage conditional on the size of the cluster it lies in. Data on natural disasters are sourced from SHELDUS, and run from 2000 though 2020.

Tables

Table 1: Summary Statistics

	Counties						
	Count	Mean	SD	Median	90th Pct.	95th Pct.	99th Pct.
Property Damage	161,664	3,613.9	154,580.5	15.8	450.6	1,425.3	18,249.3
Crop Damage	161,664	413.8	9,368.8	0.0	0.0	51.4	6,320.9
Total Damage	161,664	4,027.6	155,071.3	19.5	666.0	2,455.1	28,129.6
Injuries	161,664	0.3	6.8	0.0	0.0	1.0	5.0
Fatalities	161,664	0.1	1.8	0.0	0.0	0.0	1.0
Size	161,664	1.0	0.0	1.0	1.0	1.0	1.0
GDP	149,031	8,495.4	27,857.5	1,369.3	18,730.0	41,368.7	109,829.3
Population	159,101	158,076.2	416,648.7	40,234.0	371,839.0	748,626.0	1,975,076.0
Wages	149,416	3,237.9	2,352.2	2,792.8	5,387.5	6,556.6	9,859.4
	Spatial Clusters						
Property Damage	37,296	15,664.7	765,883.9	21.9	1,032.6	4,144.2	74,840.0
Crop Damage	37,296	1,793.5	44,856.2	0.0	0.0	40.5	7,990.4
Total Damage	37,296	17,458.2	777,418.7	23.6	1,230.1	5,555.8	116,869.9
Injuries	37,296	1.5	25.8	0.0	1.0	3.0	23.0
Fatalities	37,296	0.3	6.0	0.0	1.0	1.0	5.0
Size	37,296	4.3	20.0	1.0	6.0	13.0	58.0
GDP	34,380	32,175.4	115,593.6	3,040.0	65,681.8	149,291.7	510,954.1
Population	36,712	643,224.6	2,388,171.1	79,821.5	1,236,064.0	2,869,672.0	9,996,678.0
Wages	34,753	3,550.8	2,103.3	3,186.9	5,731.4	6,768.5	9,436.6

Notes: This table shows summary statistics of the fatalities, injuries, property damage, crop damage, and total (property and crop) damage from natural disasters, aggregated to the county- and spatial cluster-levels, as well as the average GDP, population, size, and wages in each of these units of aggregation. GDP totals are annual, and in millions of USD. Wage totals are quarterly per-capita. Population figures are annual. Damage totals are in thousands of inflation-adjusted USD, and include property and crop damages. Damages, injuries, and fatalities data are sourced from SHELDUS, and run from 2000 through 2020. GDP data are sourced from the Bureau of Economic Analysis. Population data are sourced from the US Census Bureau's Annual Community Survey (ACS). Wages data are sourced from the Quarterly Census of Employment and Wages (QCEW).

Table 2: Differences in Total Damages According to Hazard Type

	Counties					Clusters				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Drought	1.801***					3.974***				
	(0.363)					(0.238)				
Heat		0.826***					0.958***			
		(0.179)					(0.189)			
Wildfire			1.688***					2.054***		
			(0.156)					(0.125)		
Flooding				1.432***					1.123***	
				(0.063)					(0.041)	
Hurricane					3.202***					2.493***
					(0.232)					(0.345)
Log GDP	0.563***	0.601***	0.587***	0.577***	0.622***	0.925***	0.952***	0.919***	0.937***	0.955***
	(0.068)	(0.069)	(0.069)	(0.071)	(0.069)	(0.073)	(0.076)	(0.075)	(0.076)	(0.076)
Log Population	-0.447***	-0.499***	-0.485***	-0.474***	-0.523***	-0.356***	-0.375***	-0.348***	-0.391***	-0.378***
	(0.071)	(0.073)	(0.073)	(0.074)	(0.073)	(0.067)	(0.070)	(0.069)	(0.069)	(0.070)
Average Wages	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	7.242***	7.319***	7.336***	7.111***	7.210***	1.480***	1.353***	1.457***	1.507***	1.328***
	(0.276)	(0.277)	(0.271)	(0.279)	(0.275)	(0.297)	(0.307)	(0.300)	(0.308)	(0.305)
Observations	134,771	134,771	134,771	134,771	134,771	29,763	29,763	29,763	29,763	29,763
R^2	0.025	0.012	0.017	0.066	0.043	0.177	0.159	0.173	0.188	0.162

Notes: This table shows the results of a regression of log of all (property and crop) damages on indicators for the presence of a hazard in a given county/cluster, with controls included as regressors. Damages, as well as control variables, are aggregated to the county/cluster level. Wages data are annual and sourced from BEA. Population data are annual and sourced from the US Census Bureau. Wages data are quarterly and sourced from the QCEW. *, **, and *** indicate 10%, 5%, and 1% significance, respectively.

Table 3: Differences in County-Level Damage By Cluster-level Damage

	Counties									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Drought=1	-5.807***	-3.875***								
	(1.169)	(0.990)								
Drought=1 × Cluster Log Damage	0.432***	0.318***								
	(0.080)	(0.065)								
Heat=1			0.286	-0.112						
			(0.744)	(0.654)						
Heat=1 × Cluster Log Damage			0.022	0.035						
			(0.050)	(0.043)						
Wildfire=1					-1.058	-0.624				
					(0.657)	(0.608)				
Wildfire=1 × Cluster Log Damage					0.200***	0.157***				
					(0.048)	(0.044)				
Flooding=1							-0.168	-0.150		
							(0.182)	(0.184)		
Flooding=1 × Cluster Log Damage							0.091***	0.087***		
							(0.013)	(0.013)		
Hurricane=1									-1.743***	-1.603***
									(0.633)	(0.555)
Hurricane=1 × Cluster Log Damage									0.182***	0.161***
									(0.032)	(0.035)
Cluster Log Damage	0.248***	0.262***	0.262***	0.274***	0.261***	0.272***	0.227***	0.240***	0.243***	0.257***
	(0.011)	(0.008)	(0.011)	(0.009)	(0.011)	(0.009)	(0.012)	(0.010)	(0.010)	(0.009)
Log GDP	0.644***	0.070	0.696***	0.069	0.682***	0.081	0.664***	0.072	0.708***	0.056
	(0.061)	(0.086)	(0.066)	(0.090)	(0.065)	(0.090)	(0.066)	(0.091)	(0.066)	(0.090)
Average Wages	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Population	-0.511***	-0.128	-0.583***	-0.088	-0.569***	-0.152	-0.549***	-0.102	-0.595***	-0.099
	(0.065)	(0.244)	(0.071)	(0.257)	(0.070)	(0.256)	(0.071)	(0.265)	(0.071)	(0.250)
County FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Date FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	115,739	115,712	115,739	115,712	115,739	115,712	115,739	115,712	115,739	115,712
R^2	0.187	0.336	0.169	0.325	0.176	0.330	0.216	0.361	0.183	0.332

Notes: This table shows the results of a regression of log of all (property and crop) damages for both county-level aggregates on indicators for the presence of a hazard in a given county/cluster along with an interaction of the damage indicator with the log of damage of that county's spatial cluster excluding that county. Damages are aggregated to the county/cluster level, and are in inflation-adjusted USD. Damages data are sourced from SHELDUS, and run from 2000 through 2020. Standard errors are double-clustered at the county- and month-level. *, **, and *** indicate 10%, 5%, and 1% significance, respectively.

Internet Appendix

IA.A Economics Literature

This internet appendix contains a broad review of the literature on natural disasters in finance and economics.[IA.1] Many of these studies take the form of panel regressions using data aggregated at the county-by-period (e.g., month, quarter, year) level, while others isolate a single natural disaster event (e.g., Hurricane Katrina) and examine how geographic variation in exposure to that event is linked to economic outcomes. Researchers tend to agree that natural disasters have broadly negative consequences for households in the short-term. However, the results vary significantly according to demographic characteristics, and are more mixed in the long-run. Much of the research on natural disasters has focused on hurricanes since they tend to be disproportionately damaging.

IA.A.1 Natural Disasters and Household Credit

It is natural to expect that natural disasters could impact household credit outcomes. On the one hand, damages from natural disasters could lead households to demand more credit. At the same time, disasters may lead to income shocks, inhibiting the ability of borrowers to repay debt. Several papers attempt to understand the overall effect of disasters on household borrowing. Numerous papers have investigated a specific natural disaster event in order to understand the impacts of natural disaster exposure on households.

Several papers examine how Hurricane Katrina affected households. For instance, Gallagher and Hartley (2017) show that in the short-run more severe flooding from Hurricane Katrina was associated with temporary increases in credit card debt and debt delinquencies, as well as temporary drops in credit scores. On the other hand, they also show that in the long-run flooding led to decreases in total debt, which the authors attribute to the use of flood insurance payouts to paydown mortgage debt. Furthermore, they find that two years after the event, non-local lenders tend to exit the market, while local lenders tend to recover to pre-Katrina levels of lending. In a subsequent analysis, Bleemer and van der Klaauw (2019) find that a decade after Hurricane Katrina, homeownership and credit insolvency rates in flooded neighborhoods remain persistently lower than in non-flooded neighborhoods. However, they find that residents in the surrounding region were better off on net, as indicated by higher rates of consumption and homeownership, lower levels of debt, and lower rates of bankruptcy and foreclosure. They find that these effects tend to favor younger and low-income residents.

Researchers found similar effects when studying Hurricane Harvey. Billings et al. (2022) use variation in flooding from Hurricane Harvey to understand the impacts of flood losses on household credit. They find that credit-constrained homeowners in flooded areas experienced significant increases in bankruptcies and delinquencies relative to those not in flooded areas, but that flood insurance ameliorated these effects. In a follow-up paper, Gallagher et al. (2023) find that for college-aged adults, the likelihood of having student debt is reduced in areas that experienced flooding compared to areas that did not, and that local university

[IA.1] See Botzen et al. (2019) for another useful review of the economics literature on natural disasters.

enrollment appears to drop in Texas counties more affected by hurricane damage. The authors propose that households experiencing flooding are less able to secure credit for additional schooling, causing them to opt out of human capital investments.

IA.A.2 Effects of Disasters on Financial Assets and Banks

Beyond the household effects, there is a literature examining the effects of natural disasters on local firms and asset prices. The literature finds evidence that firms are negatively affected by natural disasters, and this is reflected in financial markets. Collier et al. (2024) find, using a sample of credit reports and FEMA flooding estimates data, that in the aftermath of Hurricane Harvey, business credit delinquencies doubled in areas exposed to more flooding damage, and that these effects are driven by independent businesses. Kruttli et al. (2023) find that the implied volatility of stock options of firms increased in advance of hurricanes affecting regions the firm has a presence in. Comparing the implied volatility to the eventual realized volatility indicates that investors underreact, although estimates of this underreaction have decreased following Hurricane Sandy.

While natural disasters have been shown to affect financial markets, the effects are less clear for banks. Correa et al. (2022) shows that corporate loan spreads for borrowers located in areas at high risk of experiencing a hurricane increase following hurricanes in other regions. This could indicate that lenders incorporate beliefs about the likelihood and severity of hurricanes in loan pricing. On the other hand, Blickle et al. (2021) find that banks are not significantly impacted by disasters. They find, using a county-level analysis, that disasters increase the demand for loans, offsetting losses and increasing profits at larger banks, while local banks seem to avoid lending in areas in which flooding is more common than official estimates. This finding is consistent with the idea that local firms can make use of local knowledge to more efficiently account for natural disaster risk. Similarly, Koetter et al. (2020) shows that local German banks lend to firms affected by flooding and Berg and Schrader (2012) shows that relationships between banks and borrowers can mitigate reductions in access to credit after volcanic eruptions in Ecuador.

IA.A.3 Disasters and Housing, Mortgage, and Insurance Markets

Given natural disasters can adversely affect household credit, it is important to understand how they affect housing markets, as well as mortgage and insurance markets. This subsection discusses effects of natural disasters on these markets, and how they can affect households' location decisions.

Several papers use FEMA flood map data to show that government mandates to purchase homeowner insurance can reduce borrower access to credit. These flood maps are particularly useful as lags in updates to the flood maps provide researchers an opportunity for identification. Sastry (2021) uses highly granular data on flood maps, home- and loan-level mortgage data, and data on insurance coverage and construction costs. Using an estimation strategy relying on the fact that government-backed flood insurance has a strict limit, they find that insurers offload flood risk both to the government through subsidized policies and to borrowers through requirements of higher down payments. They also show that updates to flood maps lead banks to reduce loan-to-value ratios while interest rates remain roughly the same. Blickle and Santos (2022) use Home Mortgage Disclosure Act (HMDA) data along with FEMA flood map data to investigate how banks adjust lending in response to levels of and changes to insurance requirements. They find that banks are less willing to lend in areas after flood maps are extended. They also find local banks are less responsive to updates to flood zone maps, suggesting that they use local knowledge to more responsively monitor true risk exposure relative to the insurance requirements. These results suggest that mandatory insurance standards may unintentionally harm low-income and low-credit borrowers.

It is not clear that insurers will continue to be willing to bear this risk. Issler et al. (2021) combines a game theoretic framework with closely matched data on fire burn areas to consider how wildfires affect housing and mortgage markets in California. Consistent with the model predictions, they find that insurance payouts cause increases in square footage and decreases in mortgage terminations in the aftermath of a fire, suggesting that insurance payouts lead to a general improvement in the value of homes. They further argue that perverse incentives to improve homes in high fire-risk areas may jeopardize the ability of insurance companies to bear the risks in the absence of the ability to raise prices. Sastry et al. (2023) use county- and zip code-level data on insurance to construct a comprehensive picture of how insurers respond to increases in hurricanes in Florida. They find that traditional insurers exit following increases in natural disasters. This leads riskier insurers to take their place, who offload the risk to both the government and mortgage lenders.

The exit of insurers is especially troubling as households are likely to demand more insurance as disaster-risk increases. Gallagher (2014) uses a community-level dataset with information on presidential disaster declarations to understand how affected households respond to flooding in their communities and unaffected households respond to flooding in other communities in their television media markets. Flooded households have a sharp spike in sign-ups for flood insurance and unaffected households in flooded media markets have a significant, though smaller increase in sign-ups. These findings indicate that households respond to information about floods by purchasing insurance. Similarly, theoretical research argues that household location decisions and home values are driven by a combination of households' beliefs about the level of flood risk and their preferences for waterfront living (Bakkensen and Barrage, 2018).

IA.A.4 Macroeconomic Effects of Natural Disasters

Intuitively, one would expect natural disasters to be a negative local shock to local economies, and there is some literature supporting this conjecture. Deryugina (2017) finds that local government expenditures appear to increase significantly in the decade of a hurricane. They also find that on average, disaster aid is not sufficient to cover the present value of natural disasters, although victims appear to be better insured than previously thought. Jerch et al. (2023) similarly finds that hurricanes reduce city- and county-level government tax revenues in the following decade. They also find that hurricanes raise municipal bond default risk, leading to ratings downgrades, further increasing municipal costs of capital. Similarly, Auh et al. (2022) shows that natural disasters reduce returns of uninsured municipal bonds in the weeks following a disaster. The authors also find heterogeneities in this effect according to disaster severity, federal aid, and local economic conditions. Similarly, Acharya et al. (2022) finds that municipal bond pricing is affected by heat stress.

Nonetheless, it is not always the case that natural disasters are a net drag on the economy, because the negative economic consequences from disasters may be offset by disaster aid and private insurance payouts. Using county-level disaster declarations data from FEMA, Tran et al. (2020) finds that total and per-capita income increase in the 8 years following natural disasters, with a temporary local employment boost followed by a long-term increase in wages. This effect appears to be increasing in the size of the disaster. Additionally, house prices tend to increase while population remains roughly constant, particularly in areas with inelastic housing supply. Similarly, Deryugina et al. (2018) finds that households exposed to Katrina appear to experience transitory reductions in income, while they actually increase their incomes over the longer term. This increase in income is especially concentrated among movers out of New Orleans. This finding on mobility is consistent with Boustan et al. (2020), which shows that severe disasters increase out-migration, although unlike Tran et al. (2020), these authors find housing costs and income growth decreased in the decade after disasters. In contrast, Kim et al. (2022) find that severe weather shocks are associated with persistent reductions in aggregate industrial production growth, and increases in unemployment and inflation.

Researchers have also examined macroeconomic effects of disasters at the country level. Skidmore and Toya (2002) finds that exposure to repeated climate disasters leads to a substitution of physical capital investment towards human capital investment, while also prompting a more frequent updating of the capital stock. Surprisingly then, higher frequency of natural disasters can boost total factor productivity. Cavallo et al. (2013) provides one explanation for the boost in total factor productivity by showing that while very large natural disasters reduce output, small disasters do not affect economic growth. These disappear; however, after, when controlling for major negative political events in the wake of these disasters. Bakkensen and Barrage (2018) also shows that cyclone risk is largest for small island nations, and otherwise is only modestly underestimated.

Overall, the economics literature finds mixed evidence on the economic consequences of natural disasters. While several papers show evidence consistent with negative effects of disasters on the economy, there is also significant work showing no strong effect, and even some work showing a positive effect. Of course, these findings are typically based on analyses from panel data, which requires assuming that natural disaster risk in one location is uncorrelated with natural disaster risk in another location. In the next section, we will review the climate science literature on natural disasters, which will allow us to interrogate whether this assumption is consistent with the realities observed by the scientific community.

IA.B Climate Science Literature

In this Internet Appendix section, we describe the scientific literature related to climate change. There is an extensive climate literature relating to the societal impacts of natural disasters which aims to understand the mechanisms and impacts of natural disasters historically, as well as to model future natural disasters and their impacts on society.

IA.B.1 Distributions of Severe Disasters Across Time and Space

A large strand of the climate literature has been devoted to understanding the spatial and temporal distributions of natural disaster damages. Much of these papers provide evidence that natural disasters are spatially and temporally linked, and can amplify the effects of subsequent disasters in nonlinear ways. One of the first papers to consider the spatial and temporal correlation between disasters was Wheater et al. (2005), which critiques methods that model individual rainstorms as discrete events. They propose that a methodology using more temporally and spatially continuous measures would provide better estimates of the true geographic distribution of flood risks.

A substantial body of literature also aims to understand the determinants of flood risk, and broadly shows that damage from flooding is conditional on local infrastructure, previous weather conditions, and the climate of nearby regions. Li et al. (2016) find when looking in Africa, that several factors determine how destructive and deadly a storm will be, conditional on the severity of rainfall. In particular, higher levels of forest coverage, as well as lower levels of urbanization and economic development were associated with an increase in the frequency of catastrophic flooding events. Fu et al. (2023) find that there have historically been significant heterogeneities in the levels and seasonality of flood risk across China, and over time. They show that the simultaneous increases in the frequency and severity of both drought and rainfall are linked via the same large-scale climate factors.

Janizadeh et al. (2021) models future flood risks in northwestern Iran using ensemble machine learning models. They find that granular data about geography (e.g., elevation, slope and proximity to rivers) as well as precipitation is important for predicting flood risk. More broadly, Merz et al. (2021) find that the rate of disastrous flooding has increased in severity with population and economic growth, as well as the frequency of severe storms. However, they suggest that the increase in the severity of storms is often partially offset by more effective flood mitigation and adaptation strategies. They suggest that, over the longer term, unanticipated floods due to anomalous atmospheric conditions interacting with an ill-equipped built environment are likely to be the largest source of damage and fatalities.

IA.B.2 Compound Events and Their Societal Effects

In the previous subsection, we discussed how disasters tend to be correlated across space and time. We now explore how the effects of different hazard types may be correlated. There is a significant literature studying how the co-occurrence of natural disasters can lead to "compound effects," where the downstream consequences of multiple disasters are greater than the sum of their parts. This could occur because experiencing multiple disasters could strain natural and institutional systems, leading them to breakdown. Much of the work relating to compound effects has been theoretical. Leonard et al. (2014) propose a framework for considering the risks and consequences of natural disasters, which rejects the conventional approach that natural disaster risks from multiple hazard types are independently distributed. They suggest that the causes of seemingly disparate hazard types are linked, which would lead compound events to be more frequent and more destructive than under existing models. The authors note that natural disasters can have long-term effects on a region's climate or conditions that can compound the effects of future disasters.[IA.2] Similarly, natural disasters can alter conditions in regions far away from where the disaster actually occurs.

In a later paper, Zscheischler et al. (2018) argues that it is important to model different hazard types as being driven by different factors. Subsequently, Zscheischler et al. (2020) identify broad categories of natural disaster compounding, including temporal compounding (i.e., multiple hazards occurring in succession) and spatial compounding (i.e., hazards in multiple connected locations). These hazards may be driven by a related cause, which can lead to greater damage. Moreover, destructive natural feedback loops and the failure of important infrastructure can result from hazards occurring nearby each other.

Some researchers have focused specifically on the compounding effects driving flooding. Wahl et al. (2015) demonstrate that the combination of tidal surge and heavy rain is especially likely to lead to coastal flooding. They also find that the risk of both tidal surge and heavy rain is especially severe on the US Atlantic/Gulf coast, and that the risk of these hazards has increased in recent years. In another investigation of flooding as an outcome of other compound events, Lian et al. (2013) finds that upstream rainfall can strain water drainage systems, leading to unanticipated flooding from high tides. Zhang et al. (2018) investigate the meteorological phenomena surrounding Hurricane Harvey, and show that urbanization exacerbated both the severity of rainfall as well as the flood risk, and that these effects combined to amplify the severity of the flooding.

IA.B.3 Future Projections of Climate Disasters

The previous subsections reviewed literature on correlations between the effects of disaster damage across space, time and hazard type. This subsection will review how scientists expect natural disaster risks to evolve in the future. Much of the literature attempts to understand how the evolution of climate change could affect realizations of natural disaster risk. These papers consider a variety of global temperature rise scenarios, incorporating knowledge on the compound effects of natural disasters.

Woodruff et al. (2013) show that under the expected rates of sea level rise, the severity of hurricanes is expected to increase, even holding constant the frequency of hurricanes. They suggest that changes in land use may ameliorate these increases, and that geography is a crucial determinant of the level of property loss given a particular event. Marsooli et al. (2019) find, modeling the trajectory of hurricane risks under anticipated sea level rise, that the compound effects of these hazards together would cause 100-year flooding to occur

[IA.2] Lange et al. (2020) also provides evidence that the frequency of compound hazards has increased as global average temperatures have risen.

annually in the Atlantic and Gulf cost regions. Lin et al. (2012) use a general circulation model (GCM) in combination with a hydrodynamic model to simulate possible surge events under different projections of climate change. They show that due to increased surge events, 100-year floods are likely to occur between 1-in-3 and 1-in-20 years by the late 2020s.

Work has also been done to understand the likelihood of the co-occurrence of extreme temperature and drought events. Ridder et al. (2022) models future changes to the spatial correlations of heatwaves and drought as well as extreme winds and precipitation. Their models suggest that these compound events will occur more frequently under all emissions scenarios, with substantial regional heterogeneity. Further examining heat-drought, Bevacqua et al. (2022) use ensemble climate models to predict the future co-occurrence of hot-dry events. Their models seem to suggest that precipitation is the main driver of the occurrence of hot-dry events because the conditional probability of at least moderate heat given drought becomes extremely high with even 2°C of warming.

On a broader level, researchers have tried to use some of the relationships between existing disaster types in order to assess the types of disaster risk increases that would be most damaging to society. Sarhadi et al. (2018) simulate the likelihood of spatial and temporal co-occurrence of natural disasters in an attempt to understand the downstream effects of a nonstationary climate, and find that climate change is likely to double the joint probability of the co-occurence of heat and dought in the same region, and broadly that it will increase the likelihood of the simultaneous co-occurrence of these stresses in multiple regions simultaneously. Zhou et al. (2023) models the future statistical dependence of temperature and precipitation extremes, and demonstrates a significant spatial correlation of these extreme events. According to their model, there is likely to be a significant increase in the simultaneous occurrence of extreme drought and flooding events that, together, will make adaptation to climate change more costly and difficult. Their findings suggest that the concurrent nature of extreme precipitation and temperature events poses substantial risks to natural ecosystems' abilities to self-regulate and act as a carbon sink, further amplifying climate change. They argue that "although future risks of climate extremes vary geographically, they are becoming more strongly interlinked through further warming with increased climate variability and spatial dependence of climate extremes." Anticipating and modeling the ways in which future disaster risks are likely to increase under plausible climate change scenarios is very important because of the threats these hazards can pose towards human society.

IA.B.4 Projected Societal Implications of Increasingly Severe Disasters

Future changes in the probabilities of extreme natural disasters are expected to have serious socioeconomic effects. Climate change is likely to threaten the reliability of the energy grid, and the spatial correlation of temperature shocks appear to be a key driver of this. Do et al. (2023) analyze power outages in the United States between 2018 and 2020 and find that outages are pervasive and widespread across the country, and that the most severe outages frequently co-occur with severe weather events. Counties within 100 miles of a tropical cyclone appear to be the most prone to power outages relative to other severe weather incidents, suggesting that natural disasters can have consequences outside of the places they most directly impact. Perera et al. (2020) model the impacts of a potential increase in the frequency of extreme heat and cold on the energy system in Sweden. They find that these extreme weather demands will lead to shocks both to energy demand and energy supply. Because of the spatial correlation of these weather shocks, strain on the entire energy system is likely to increase. Stone Jr et al. (2021) examine the potential for electrical grid failure under extreme heat events in the United States. They find that in recent years, power grid blackouts have increased in frequency as simultaneous heatwaves in multiple regions have placed unanticipated strain on energy systems. Under modeled heatwave scenarios, their findings suggest that spatial compounding is likely to play a significant role in triggering a rise in the frequency of widespread blackouts. Ultimately, their findings suggest that a much greater share of the urban population is likely to face an elevated risk of heat exhaustion and heat stroke relative to the present.

Climate change can also threaten food production systems due to both heat and drought events. Tigchelaar et al. (2018) argue corn production will likely be adversely affected by increased global frequencies of heat-drought events. Their research suggests that, absent technological change enabling the growth of corn under higher heat scenarios, major disruptions in the global supply of corn would become a regular occurrence under a 4°C warming scenario, with especially severe consequences for low- and middle-income countries. Thiery et al. (2021) take a more holistic approach, investigating how many extreme events the average person in a given generation will expect to experience over their lifetime. They find that expected lifetime exposure to heat waves, crop failures, droughts, and river flooding has increased significantly for current birth cohorts (those born after 2020). However, they note that the degree of these increases is highly sensitive to the degree of warming, and suggest that failing to take into account compounding effects may lead to underestimating the true increase in severe disaster risk.

Many models of future climate risks aim to understand the potential threat of multiple simultaneous shocks to key economic systems. Climate change is expected to compromise the reliability of energy grids, with spatially correlated temperature extremes increasing both energy demand and supply challenges. Additionally, the compounding effects of heat and drought are likely to significantly impact food production, such as for crops like corn, with potential disruptions becoming more common under higher warming scenarios. Ultimately, the cumulative effects of extreme climate events, amplified by compounding effects, are expected to increase significantly for future generations.

IA.C Additional Tables and Figures

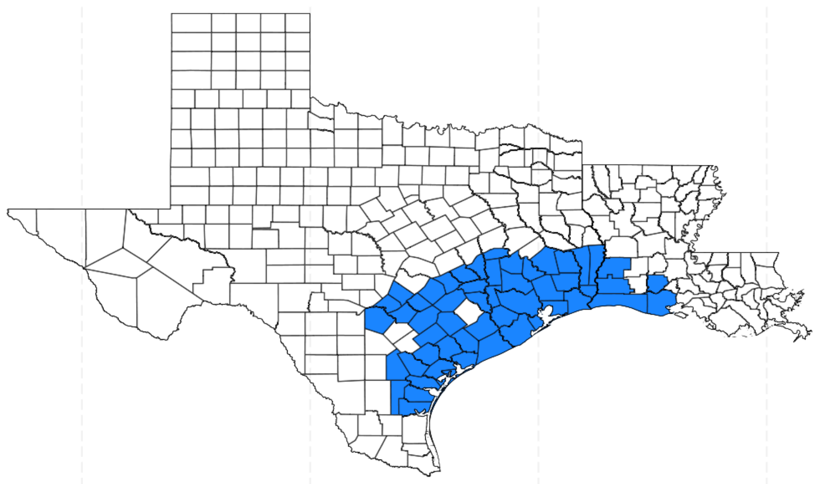


Figure IA.1: Spatiotemporal Cluster Containing Harris County, April-October 2017

This figure illustrates the entire set of counties that are included in the Harris County April-October 2017 spatiotemporal cluster, obtained following the process outlined in subsubsection 1.2.2.

Figure IA.2: Temporal Evolution of Harris County Spatiotemporal Cluster, 04-10/2017

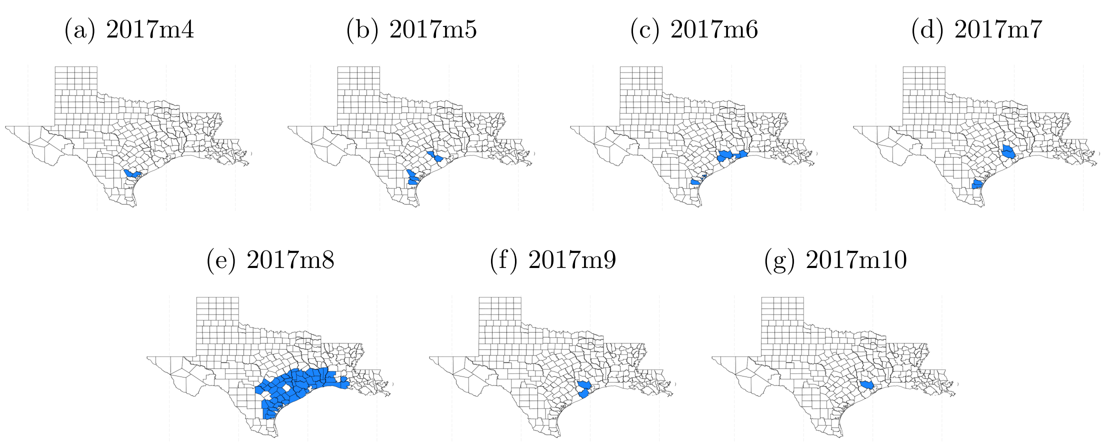
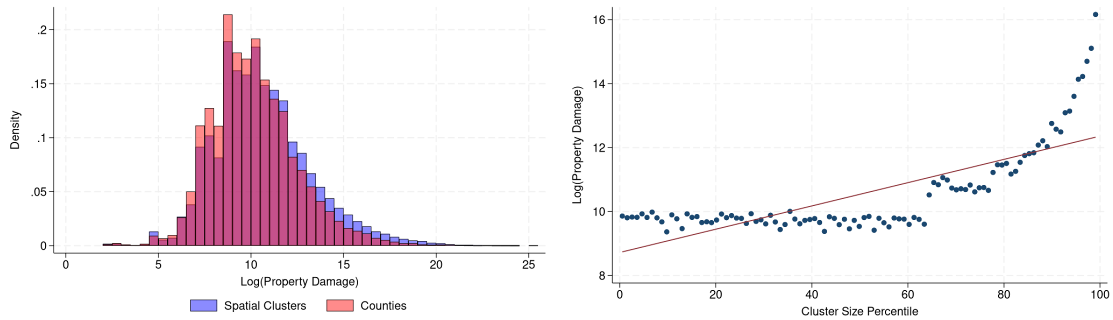


Figure IA.3: Distribution of Property Damage Across Spatial Clusters

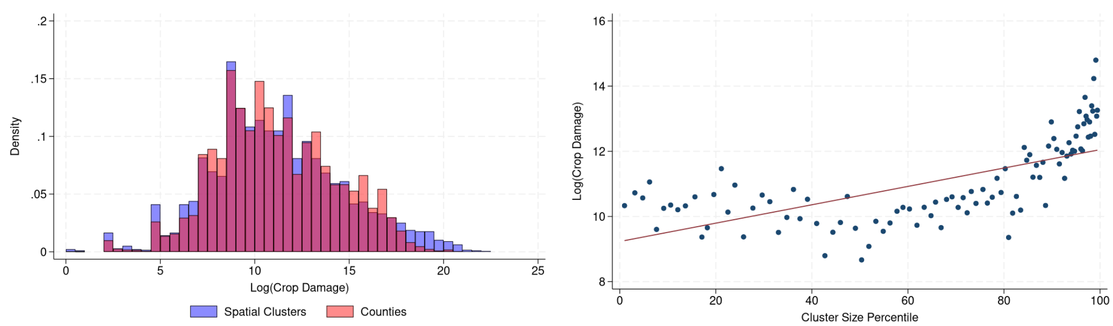
(a) Property Damage Histogram (b) Size vs Log(Property Damage)



Notes: Panel (a) compares the distributions of the log of property damages, based on whether they are aggregated to the county level or to the spatial cluster level, following the process outlined in subsubsection 1.2.1. Panel (b) shows the expected log property damages conditional on the size of the spatiotemporal cluster it lies in. Data on natural disasters are sourced from SHELDUS, and run from 2000 though 2020.

Figure IA.4: Distribution of Crop Damage Across Spatial Clusters

(a) Crop Damage Histogram (b) Size vs Log(Crop Damage)

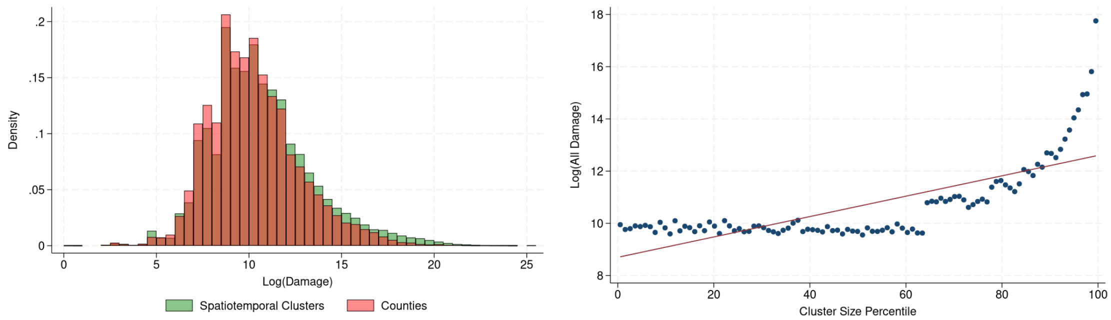


Notes: Panel (a) compares the distributions of the log of crop damages, based on whether they are aggregated to the county level or to the spatial cluster level, following the process outlined in subsubsection 1.2.1. Panel (b) shows the expected log crop damages conditional on the size of the spatiotemporal cluster it lies in. Data on natural disasters are sourced from SHELDUS, and run from 2000 though 2020.

Figure IA.5: Distribution of Total Damage Across Spatiotemporal Clusters

(a) Damage Histogram

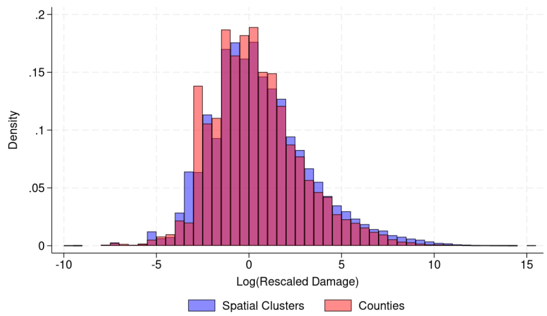
(b) Size vs Log(Damage)



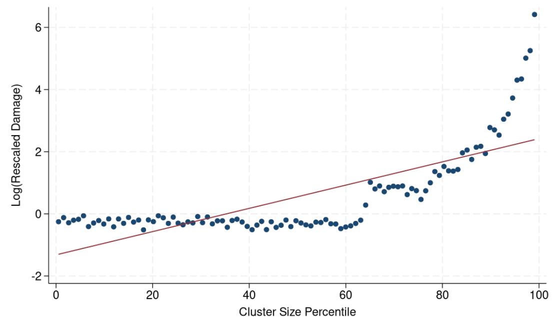
Notes: Panel (a) compares the distributions of the log of total damages, based on whether they are aggregated to the county level or to the spatiotemporal cluster level, following the process outlined in subsubsection 1.2.2. Panel (b) shows the expected log total damage conditional on the size of the spatiotemporal cluster it lies in. Data on natural disasters are sourced from SHELDUS, and run from 2000 though 2020.

Figure IA.6: Distributions of Damage Scaled by the Sample Median Across Clusters

(a) Damage Histogram



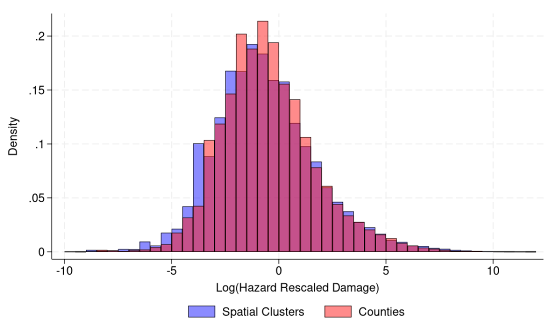
(b) Size vs Log(Damage)



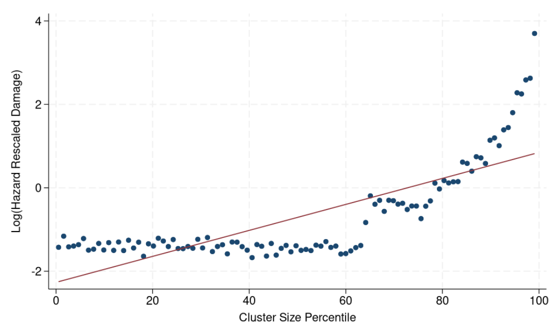
Notes: This figure displays information on the distribution of damages scaled by the median across clusters. Panel (a) shows the distribution of the log of total damages scaled by the sample median defined at the cluster-level, alongside the distribution of the log of total damages scaled by the sample median defined at the county-level. Panel (b) shows the expected log damage conditional on the size of the cluster it lies in. Data on natural disasters are sourced from SHELDUS, and run from 2000 though 2020.

Figure IA.7: Distributions of Damage Scaled by the Sum of Hazard-Specific Medians Across Clusters

(a) Damage Histogram



(b) Size vs Log(Damage)



Notes: This figure displays information on the distribution of damages, where the damages are scaled by the sum of all hazard-specific medians for all hazards included in each cluster. Panel (a) shows the distribution of the log of total damages scaled by the sample median defined at the cluster-level, alongside the distribution of the log of total damages scaled by the sample median defined at the county-level. Panel (b) shows the expected log damage conditional on the size of the cluster it lies in. Data on natural disasters are sourced from SHELDUS, and run from 2000 though 2020.

Table IA.1: Summary Statistics on Total Disaster Damages by Hazard – County-Level Data

	All Damage (thousands of $)						
	Count	Mean	SD	P50	P90	P95	P99
Hurricane	2,907	116,401.4	1,078,979.7	304.4	51,132.7	187,899.4	2,013,905.6
Earthquake	112	60,860.6	275,912.3	10,256.4	20,398.4	76,109.1	1,019,616.2
Heat	1,513	21,639.4	574,761.9	0.0	412.3	1,520.7	57,385.8
Coastal	1,539	21,458.9	481,718.2	0.0	222.0	1,517.0	23,487.4
Wildfire	2,280	18,542.7	233,944.5	85.9	4,349.4	13,983.5	285,734.3
Landslide	976	16,201.0	213,895.4	23.1	3,377.8	18,261.2	142,381.2
Tornado	11,847	11,807.7	327,615.9	140.0	3,166.9	9,929.7	108,074.9
Flooding	30,597	11,764.9	327,334.3	69.4	2,361.9	7,465.0	75,000.0
Drought	3,879	9,600.3	55,307.1	146.9	18,020.7	29,140.6	130,019.7
Lightning	9,861	4,370.6	103,756.7	38.5	627.9	1,568.6	22,275.0
Hail	13,174	4,299.6	81,688.3	57.7	1,866.3	6,447.5	54,917.8
Volcano	19	2,441.0	6,788.8	55.5	16,054.7	26,097.2	26,097.2
Tsunami	58	2,303.6	8,368.6	166.6	6,409.1	9,368.9	60,918.0
Winter	14,105	1,785.9	25,599.7	50.6	1,400.1	3,887.1	28,121.2
Wind	102,856	1,524.8	67,663.9	14.7	304.7	1,010.0	11,510.6
Thunderstorm	78,705	1,304.2	39,884.1	16.0	314.1	998.3	12,090.3
Fog	317	374.8	2,084.0	50.1	555.2	1,156.9	6,597.7
Avalanche	1,055	354.2	7,399.2	0.0	16.6	111.8	2,529.1

Notes: This table shows summary statistics of total damages from natural disasters by disaster-type, aggregated to the county level. All Damage totals are in thousands of inflation-adjusted USD, and include property and crop damages. Damages data are sourced from SHELDUS, and run from 2000 through 2020.

Table IA.2: Summary Statistics on Total Disaster Damages by Hazard – Spatial Cluster-Level Data

	All Damage (thousands of $)						
	Count	Mean	SD	P50	P90	P95	P99
Hurricane	251	1,515,411.8	9,206,264.8	402.4	717,977.0	5,183,330.6	28754559.3
Drought	316	282,780.4	1,467,953.3	6,648.5	468,473.7	1,023,147.6	7,404,489.6
Earthquake	28	243,551.9	855,175.1	1,387.6	775,056.4	800,000.0	4,468,203.6
Heat	756	217,200.3	3,502,643.5	0.0	14,184.5	81,492.4	2,725,001.8
Landslide	548	191,678.5	1,657,752.1	63.1	33,485.2	193,630.8	4,468,203.6
Coastal	967	177,302.4	3,219,685.8	0.0	4,499.4	28,905.7	1,168,300.2
Tornado	4,443	95,185.1	2,154,472.4	217.1	19,371.8	76,109.1	947,638.0
Wildfire	1,061	65,565.3	644,749.1	256.4	24,307.3	94,620.1	1,624,240.5
Flooding	7,836	64,262.7	1,674,410.3	87.4	9,133.1	38,130.5	479,159.0
Hail	4,359	58,071.9	1,579,582.4	103.7	18,369.7	74,124.2	617,133.1
Lightning	5,684	55,398.8	1,465,435.3	54.2	5,016.8	29,528.4	468,473.7
Thunderstorm	15,783	30,499.4	1,166,570.8	26.8	1,783.0	8,963.9	194,103.9
Avalanche	333	29,874.3	410,041.4	0.0	998.8	11,759.7	230,797.9
Fog	158	28,271.8	165,974.5	126.4	13,243.5	98,944.2	870,080.4
Wind	19,136	25,842.4	1,059,512.1	24.0	1,509.5	7,407.6	169,508.6
Tsunami	32	21,282.6	37,244.0	2,451.9	93,238.3	123,556.2	126,338.0
Winter	2,227	19,724.0	204,289.9	61.1	10,131.0	41,626.6	395,161.7
Volcano	11	4,216.2	8,645.4	444.0	16,054.7	26,097.2	26,097.2
	Cluster Size (# of Counties)						
Tsunami	32	44.7	77.6	3.5	189.0	233.0	270.0
Drought	316	29.7	88.5	6.5	55.0	89.0	368.0
Hurricane	251	24.0	63.8	2.0	47.0	171.0	309.0
Heat	756	19.8	76.2	1.0	33.0	99.0	380.0
Landslide	548	18.2	66.8	1.0	27.0	55.0	384.0
Tornado	4,443	14.9	53.1	1.0	30.0	71.0	242.0
Hail	4,359	14.4	52.1	1.0	30.0	62.0	240.0
Fog	158	13.4	74.0	2.0	20.0	39.0	90.0
Coastal	967	13.3	67.2	1.0	13.0	46.0	309.0
Avalanche	333	12.4	76.9	3.0	11.0	17.0	240.0
Winter	2,227	12.3	39.9	2.0	31.0	52.0	173.0
Lightning	5,684	11.8	46.9	1.0	22.0	53.0	216.0
Flooding	7,836	11.1	41.4	1.0	23.0	47.0	185.0
Wildfire	1,061	11.0	56.2	1.0	18.0	34.0	208.0
Thunderstorm	15,783	7.0	29.8	1.0	11.0	26.0	106.0
Wind	19,136	6.6	27.4	1.0	11.0	24.0	91.0
Earthquake	28	4.2	14.5	1.0	4.0	9.0	78.0
Volcano	11	1.7	2.1	1.0	2.0	8.0	8.0

Notes: This table shows summary statistics of damages and cluster sizes from natural disasters by disaster-type, aggregated to the spatial cluster level. All Damage totals are in thousands of inflation-adjusted USD, and include property and crop damages. Damages data are sourced from SHELDUS, and run from 2000 through 2020.

Table IA.3: Summary Statistics on Property and Crop Damage by Hazard – County-Level Data

	Property Damage (thousands of $)						
	Count	Mean	SD	P50	P90	P95	P99
Hurricane	2,907	112289200.8	1.1e+09	250,000.0	38958251.8	152580213.6	2.0e+09
Earthquake	112	60860596.6	275912311.8	10256410.3	20398415.6	76109071.0	1.0e+09
Coastal	1,539	21328717.9	481720028.4	0.0	181,188.7	1,105,167.1	21839296.5
Heat	1,513	21048272.6	574728609.3	0.0	263,646.0	891,070.2	7,663,818.6
Wildfire	2,280	17485988.0	232077677.5	71,676.3	3,918,637.5	12004120.4	167726381.0
Landslide	976	16027641.2	213651834.7	22,311.5	3,222,129.7	17673373.3	142381223.5
Tornado	11,847	11393616.4	327218848.7	132,739.9	2,764,776.8	8,444,576.0	100010000.0
Flooding	30,597	11279870.4	327081581.3	61,089.6	1,822,515.7	5,689,910.6	64808014.2
Lightning	9,861	4,176,031.7	102742277.3	37,001.6	585,571.7	1,403,953.7	16584008.0
Hail	13,174	3,699,507.5	81315226.5	36,425.7	890,499.4	3,019,811.5	50086453.4
Tsunami	58	2,272,505.7	8,345,215.8	166,647.2	6,409,106.6	8,739,690.8	60917975.3
Drought	3,879	1,650,004.9	25061334.0	0.0	153,818.6	742,621.9	18034970.9
Wind	102,856	1,330,726.7	67297076.6	14,064.8	260,039.3	740,032.9	7,548,161.3
Winter	14,105	1,233,793.6	23502167.9	38,054.5	765,452.8	2,250,369.3	20770468.0
Thunderstorm	78,705	1,124,336.6	39481406.8	15,171.6	260,964.1	712,281.6	7,400,328.6
Volcano	19	888,129.4	3,672,941.3	55,502.5	148,006.6	16054739.4	16054739.4
Fog	317	355,622.2	2,057,396.4	49,384.8	527,814.2	1,118,295.6	4,792,807.0
Avalanche	1,055	353,879.4	7,399,243.4	0.0	15,272.4	101,144.2	2,529,109.9
	Crop Damage (thousands of $)						
Drought	3,879	7,950,303.5	47015111.0	53,631.0	16813546.7	28144643.4	80528307.3
Hurricane	2,907	4,112,170.0	27523193.0	0.0	805,283.1	20877127.3	98255592.7
Volcano	19	1,552,827.6	5,958,626.7	0.0	1,221,792.2	26096409.1	26096409.1
Wildfire	2,280	1,056,716.1	28018097.5	0.0	6,430.2	64,550.4	10930439.9
Hail	13,174	600,049.8	5,851,991.3	0.0	284,912.6	1,165,292.1	15670195.9
Heat	1,513	591,150.3	7,613,529.0	0.0	0.0	58,264.6	4,661,168.4
Winter	14,105	552,087.5	10092482.9	0.0	0.0	114,166.6	7,585,092.5
Flooding	30,597	485,030.4	7,629,397.5	0.0	21,452.4	291,323.0	10267359.2
Tornado	11,847	414,048.0	8,837,408.0	0.0	12,020.8	159,575.2	3,653,553.6
Lightning	9,861	194,576.2	4,272,883.9	0.0	0.0	1,105.9	728,514.8
Wind	102,856	194,095.6	6,049,553.6	0.0	0.0	6,087.2	1,221,792.2
Thunderstorm	78,705	179,834.7	4,449,395.3	0.0	0.0	12,174.5	1,460,934.4
Landslide	976	173,324.8	2,023,756.5	0.0	0.0	11,072.2	8,667,977.5
Coastal	1,539	130,149.1	1,787,798.5	0.0	0.0	0.0	534,211.2
Tsunami	58	31,141.4	237,166.0	0.0	0.0	0.0	1,806,202.8
Fog	317	19,183.9	214,798.5	0.0	0.0	5,708.3	177,607.9
Avalanche	1,055	317.5	6,639.1	0.0	0.0	0.0	0.0
Earthquake	112	0.0	0.0	0.0	0.0	0.0	0.0

Notes: This table shows summary statistics of property and crop damage from natural disasters by disaster-type, aggregated to the county level. All Damage totals are in thousands of inflation-adjusted USD, and include property and crop damages. Damages data are sourced from SHELDUS, and run from 2000 through 2020.

Table IA.4: Summary Statistics on Property and Crop Damage by Hazard – Spatial Cluster-Level Data

	Property Damage (thousands of $)						
	Count	Mean	SD	P50	P90	P95	P99
Hurricane	251	1.5e+09	9.1e+09	394,452.3	522450111.1	4.8e+09	2.9e+10
Earthquake	28	243551914.6	855175117.3	1,387,610.6	775056385.2	800000000.3	4.5e+09
Heat	756	202426875.3	3.5e+09	0.0	11140750.7	47055820.9	2.6e+09
Drought	316	180844672.1	1.4e+09	78,088.3	51741923.6	250909530.4	7.4e+09
Landslide	548	176903602.3	1.6e+09	59,019.6	30544805.8	152162263.1	4.0e+09
Coastal	967	170655933.4	3.2e+09	0.0	3,988,351.0	21839296.5	725038628.0
Tornado	4,443	89816750.7	2.1e+09	206,965.7	14818436.1	57143538.6	685012082.3
Flooding	7,836	60000233.9	1.7e+09	78,762.9	7,516,921.7	30128218.0	444015000.0
Wildfire	1,061	57019350.5	634813771.4	210,172.4	18868000.0	62445467.0	1.1e+09
Hail	4,359	52252693.0	1.5e+09	67,198.6	11298923.6	49137744.7	523857381.3
Lightning	5,684	52187550.3	1.4e+09	53,181.9	4,068,965.4	21042561.2	435289331.3
Avalanche	333	28903357.8	406823959.9	0.0	890,476.1	8,991,520.1	230797874.7
Thunderstorm	15,783	28062604.1	1.2e+09	25,957.4	1,503,027.3	6,815,850.0	137272159.7
Wind	19,136	23621053.3	1.0e+09	22,849.0	1,260,330.7	5,661,042.0	112254918.9
Tsunami	32	20737956.9	37323667.3	412,871.3	91432080.2	123556183.1	126338031.8
Fog	158	18664638.9	94003543.6	119,714.7	9,951,998.9	98931859.9	536298604.9
Winter	2,227	15783781.3	196678579.8	51,956.9	6,008,469.1	23240915.7	267988338.1
Volcano	11	1,534,041.6	4,817,810.7	11,416.7	444,019.7	16054739.4	16054739.4
	Crop Damage (thousands of $)						
Drought	316	101935705.7	309370829.2	1,869,448.0	260039326.0	545714553.5	1.2e+09
Hurricane	251	52840149.8	336693667.7	0.0	15434592.2	186448194.3	1.0e+09
Landslide	548	14774881.3	166374829.1	0.0	33,553.5	786,757.8	257959011.1
Heat	756	14773417.9	143724572.4	0.0	14,800.7	2,062,567.0	347932618.2
Fog	158	9,607,193.2	101568810.2	0.0	71,228.2	14278890.9	79876542.6
Wildfire	1,061	8,545,914.9	109268665.2	0.0	54,785.0	1,300,196.6	134452905.6
Coastal	967	6,646,429.7	75376785.1	0.0	0.0	188,704.0	69204784.6
Hail	4,359	5,819,248.0	73221039.9	0.0	693,943.9	4,478,938.4	82608621.9
Tornado	4,443	5,368,300.3	64822316.1	0.0	114,166.6	1,954,867.6	79876542.6
Flooding	7,836	4,262,488.2	80100542.7	0.0	37,541.7	753,085.9	47258037.1
Winter	2,227	3,940,183.8	50781136.4	0.0	0.0	379,256.9	75201312.0
Lightning	5,684	3,211,239.5	49983313.5	0.0	4,203.4	337,555.4	41063036.1
Volcano	11	2,682,156.7	7,783,153.4	0.0	1,221,792.2	26096409.1	26096409.1
Thunderstorm	15,783	2,436,809.6	50998965.4	0.0	562.6	107,262.0	15049747.4
Wind	19,136	2,221,358.8	48236527.9	0.0	0.0	58,848.2	13471657.6
Avalanche	333	970,931.9	14317655.5	0.0	0.0	0.0	1,129,367.9
Tsunami	32	544,662.4	2,408,875.7	0.0	0.0	2,151,336.4	13471657.6
Earthquake	28	0.0	0.0	0.0	0.0	0.0	0.0

Notes: This table shows summary statistics of injuries and fatalities from natural disasters by disaster-type, aggregated to the spatial cluster level. All Damage totals are in thousands of inflation-adjusted USD, and include property and crop damages. Damages data are sourced from SHELDUS, and run from 2000 through 2020.

Table IA.5: Summary Statistics on Injuries and Fatalities by Hazard – County-Level Data

	Count	Mean	SD	P50	P90	P95	P99
	Fatalities						
Heat	1,513	1.7	4.7	1.0	3.0	6.0	21.0
Coastal	1,539	0.8	1.1	1.0	2.0	2.0	4.0
Hurricane	2,907	0.5	12.4	0.0	0.0	1.0	3.0
Landslide	976	0.4	3.2	0.0	0.3	1.0	6.0
Avalanche	1,055	0.3	0.4	0.2	0.9	1.0	2.0
Wildfire	2,280	0.2	1.7	0.0	0.0	1.0	5.3
Volcano	19	0.2	0.7	0.0	1.0	3.0	3.0
Fog	317	0.2	0.7	0.0	1.0	1.0	2.0
Lightning	9,861	0.2	2.0	0.0	0.0	1.0	2.0
Tornado	11,847	0.2	1.9	0.0	0.0	1.0	3.0
Flooding	30,597	0.1	3.9	0.0	0.0	0.4	2.0
Earthquake	112	0.1	0.4	0.1	0.2	0.3	2.0
Winter	14,105	0.1	0.4	0.0	0.0	0.8	2.0
Wind	102,856	0.0	0.8	0.0	0.0	0.0	1.0
Thunderstorm	78,705	0.0	0.9	0.0	0.0	0.0	1.0
Hail	13,174	0.0	0.6	0.0	0.0	0.0	1.0
Tsunami	58	0.0	0.1	0.0	0.0	0.5	0.5
Drought	3,879	0.0	0.3	0.0	0.0	0.0	1.0
	Injuries						
Heat	1,513	9.4	40.8	0.0	17.0	40.0	213.0
Earthquake	112	2.9	16.9	0.0	1.0	20.0	30.0
Wildfire	2,280	1.8	17.5	0.0	2.0	4.0	20.0
Tornado	11,847	1.8	17.6	0.0	2.0	6.0	31.0
Fog	317	1.7	5.2	0.0	4.0	10.0	30.0
Volcano	19	1.4	5.3	0.0	3.0	23.0	23.0
Lightning	9,861	0.9	15.4	0.0	1.0	3.0	9.0
Coastal	1,539	0.8	2.9	0.0	2.0	4.0	10.0
Hurricane	2,907	0.7	15.0	0.0	0.0	1.0	5.0
Landslide	976	0.7	7.3	0.0	0.2	2.0	12.0
Drought	3,879	0.3	10.4	0.0	0.0	0.0	1.0
Thunderstorm	78,705	0.3	7.1	0.0	0.0	0.0	3.0
Hail	13,174	0.3	3.0	0.0	0.0	0.0	5.0
Avalanche	1,055	0.3	0.8	0.0	0.7	1.0	2.7
Winter	14,105	0.2	4.0	0.0	0.0	0.0	4.0
Wind	102,856	0.2	6.3	0.0	0.0	0.0	3.0
Flooding	30,597	0.2	3.8	0.0	0.0	0.0	3.0
Tsunami	58	0.1	0.4	0.0	0.0	1.0	2.0

Notes: This table shows summary statistics of injuries and fatalities from natural disasters by disaster-type, aggregated to the county level. All Damage totals are in thousands of inflation-adjusted USD, and include property and crop damages. Damages data are sourced from SHELDUS, and run from 2000 through 2020.

Table IA.6: Summary Statistics on Injuries and Fatalities by Hazard – Spatial Cluster-Level Data

	Fatalities						
	Count	Mean	SD	P50	P90	P95	P99
Hurricane	251	6.9	64.0	0.0	6.0	14.0	82.0
Heat	756	4.4	12.6	1.0	9.0	19.0	59.0
Drought	316	2.8	25.4	0.0	2.0	5.0	35.0
Avalanche	333	2.8	22.5	1.0	3.0	4.1	19.0
Landslide	548	2.6	13.2	0.0	3.0	10.0	82.0
Coastal	967	2.4	14.1	1.0	3.0	5.0	27.0
Wildfire	1,061	1.7	14.3	0.0	1.0	5.0	38.0
Tornado	4,443	1.1	17.0	0.0	1.0	3.0	19.0
Fog	158	1.0	3.0	0.0	2.0	5.0	16.0
Lightning	5,684	1.0	15.1	0.0	1.0	2.0	15.0
Hail	4,359	1.0	17.1	0.0	0.0	2.0	15.0
Flooding	7,836	0.8	13.0	0.0	1.0	2.0	13.0
Winter	2,227	0.8	8.7	0.0	2.0	3.0	8.0
Tsunami	32	0.5	1.2	0.0	2.5	4.0	4.0
Earthquake	28	0.5	1.3	0.0	2.0	3.0	5.9
Thunderstorm	15,783	0.4	9.1	0.0	0.0	1.0	6.0
Wind	19,136	0.4	8.3	0.0	0.0	1.0	6.0
Volcano	11	0.4	0.9	0.0	1.0	3.0	3.0
	Injuries						
Heat	756	23.5	98.1	0.0	47.0	98.0	450.0
Drought	316	23.3	230.7	0.0	4.0	19.0	349.0
Avalanche	333	13.1	200.4	0.0	3.0	8.0	38.0
Earthquake	28	11.6	33.1	0.0	30.0	40.0	172.0
Wildfire	1,061	10.2	119.2	0.0	7.0	21.0	153.0
Hurricane	251	9.8	58.0	0.0	8.0	30.0	300.0
Coastal	967	8.0	120.1	0.0	6.0	13.0	61.0
Fog	158	7.3	22.0	0.0	22.0	40.0	101.0
Landslide	548	7.1	73.7	0.0	5.0	14.0	85.0
Tornado	4,443	6.5	67.1	0.0	8.0	21.0	102.0
Hail	4,359	4.8	65.2	0.0	3.0	11.0	87.0
Lightning	5,684	4.4	58.9	0.0	4.0	10.0	63.0
Winter	2,227	4.1	79.7	0.0	3.0	7.0	47.0
Tsunami	32	3.9	10.9	0.0	11.0	24.0	54.0
Flooding	7,836	3.2	50.1	0.0	2.0	6.0	56.0
Volcano	11	2.5	6.9	0.0	3.0	23.0	23.0
Thunderstorm	15,783	2.1	37.2	0.0	1.0	4.0	31.0
Wind	19,136	1.9	33.9	0.0	1.0	3.0	27.0

Notes: This table shows summary statistics of injuries and fatalities from natural disasters by disaster-type, aggregated to the spatial cluster level. All Damage totals are in thousands of inflation-adjusted USD, and include property and crop damages. Damages data are sourced from SHELDUS, and run from 2000 through 2020.

Table IA.7: Summary Statistics on Total Disaster Damages by Hazard – Spatiotemporal Cluster-Level Data

	All Damage (thousands of $)						
	Count	Mean	SD	P50	P90	P95	P99
Hurricane	205	1,963,249.8	10233478.9	770.2	2,479,581.6	9,103,685.5	28836436.1
Drought	287	898,143.5	6,440,464.2	34,090.7	1,006,839.9	2,137,319.8	22814845.2
Heat	581	321,479.4	4,020,061.0	0.0	86,286.5	330,235.7	7,884,366.7
Coastal	914	293,508.1	3,474,335.0	0.0	47,078.6	289,351.0	7,427,618.9
Landslide	531	281,027.7	1,876,897.3	142.0	119,935.3	516,826.3	7,884,366.7
Earthquake	28	244,245.6	854,974.6	10,090.4	775,056.4	800,000.0	4,468,203.6
Tornado	3,601	140,534.5	2,473,059.3	208.6	33,286.5	147,319.8	1,446,102.8
Hail	3,275	110,779.0	1,970,065.6	110.6	40,033.3	158,066.1	1,436,114.5
Wildfire	1,010	97,283.6	752,906.6	353.6	41,583.8	236,637.1	2,283,272.1
Flooding	5,647	92,928.0	1,987,866.1	78.3	15,826.3	70,442.4	910,873.6
Lightning	4,318	89,451.9	1,743,610.9	50.2	10,003.3	70,677.2	1,053,624.8
Fog	155	61,794.1	252,195.4	380.5	121,939.8	280,777.7	1,810,372.9
Tsunami	28	51,198.7	92,339.7	11,410.7	170,003.3	171,338.9	426,637.6
Thunderstorm	11,598	44,486.3	1,374,608.5	23.3	2,111.5	14,613.0	349,048.6
Wind	14,399	36,436.1	1,233,626.1	20.9	1,538.8	10,623.7	288,607.9
Winter	1,914	33,297.2	267,370.3	62.9	19,040.3	86,601.0	688,621.7
Avalanche	324	32,434.4	417,199.3	0.1	3,135.3	21,368.4	264,194.4
Volcano	11	4,216.2	8,645.4	444.0	16,054.7	26,097.2	26,097.2
	Cluster Size						
Drought	287	123.7	230.0	16.0	429.0	641.0	1,038.0
Tsunami	28	90.8	136.7	7.0	297.0	321.0	510.0
Hurricane	205	80.4	169.4	2.0	356.0	527.0	633.0
Heat	581	62.5	174.5	2.0	205.0	492.0	854.0
Landslide	531	47.7	147.4	2.0	86.0	342.0	842.0
Coastal	914	46.2	148.1	1.0	77.0	403.0	754.0
Fog	155	40.9	126.9	4.0	68.0	333.0	546.0
Hail	3,275	27.8	100.1	1.0	43.0	145.0	552.0
Tornado	3,601	26.9	97.2	1.0	40.0	144.0	545.0
Wildfire	1,010	25.0	108.9	2.0	24.0	86.0	567.0
Winter	1,914	21.4	68.9	2.0	46.0	103.0	358.0
Lightning	4,318	21.4	88.1	1.0	23.0	91.0	510.0
Flooding	5,647	19.4	78.9	1.0	26.0	76.0	451.0
Avalanche	324	17.1	87.7	4.0	16.0	27.0	456.0
Thunderstorm	11,598	10.7	55.9	1.0	10.0	27.0	277.0
Wind	14,399	9.4	50.4	1.0	10.0	23.0	215.0
Earthquake	28	6.0	15.2	1.0	17.0	23.0	78.0
Volcano	11	1.7	2.1	1.0	2.0	8.0	8.0

Notes: This table shows summary statistics of damages and cluster sizes from natural disasters by disaster-type, aggregated to the spatiotemporal cluster level, conditional on the presence of the given hazard. All Damage totals are in thousands of inflation-adjusted USD, and include property and crop damages. Damages data are sourced from SHELDUS, and run from 2000 through 2020.

Table IA.8: Differences in Injuries According to Hazard Type

	Counties					Clusters				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Drought	0.127					4.894				
	(0.255)					(3.471)				
Heat		8.054***					18.585***			
		(1.972)					(3.123)			
Wildfire			1.728**					4.485***		
			(0.707)					(1.282)		
Flooding				-0.088**					0.446*	
				(0.041)					(0.233)	
Hurricane					0.300					4.733
					(0.339)					(4.571)
Log GDP	0.077***	0.053**	0.063**	0.081***	0.081***	0.803***	0.690***	0.747***	0.833***	0.835***
	(0.029)	(0.024)	(0.027)	(0.029)	(0.028)	(0.138)	(0.122)	(0.140)	(0.138)	(0.137)
Log Population	0.071**	0.064**	0.082***	0.065**	0.065**	0.152	0.074	0.200*	0.127	0.124
	(0.030)	(0.028)	(0.030)	(0.027)	(0.027)	(0.102)	(0.097)	(0.107)	(0.098)	(0.100)
Average Wages	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.572***	-1.204***	-1.513***	-1.559***	-1.576***	-12.039***	-9.761***	-11.851***	-12.217***	-12.162***
	(0.324)	(0.256)	(0.300)	(0.320)	(0.321)	(1.385)	(1.137)	(1.403)	(1.425)	(1.401)
Observations	134,771	134,771	134,771	134,771	134,771	32,492	32,492	32,492	32,492	32,492
R^2	0.001	0.009	0.002	0.001	0.001	0.015	0.046	0.017	0.014	0.015

Notes: This table shows the results of a regression of counts of injuries on indicators for the presence of a hazard in a given county/cluster. Counts of injuries are aggregated to the county/cluster level. Injuries data are sourced from SHELDUS, and run from 2000 through 2020.

Table IA.9: Differences in Fatalities According to Hazard Type

	Counties					Clusters				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Drought	-0.015					0.477*				
	(0.014)					(0.281)				
Heat		2.179***					3.208***			
		(0.614)					(0.358)			
Wildfire			0.180**					0.913***		
			(0.078)					(0.236)		
Flooding				0.097**					0.236***	
				(0.039)					(0.037)	
Hurricane					0.520					2.058**
					(0.377)					(0.807)
Log GDP	0.033	0.025	0.030	0.030	0.035	0.110***	0.087***	0.094***	0.110***	0.112***
	(0.025)	(0.025)	(0.025)	(0.024)	(0.027)	(0.019)	(0.017)	(0.019)	(0.018)	(0.018)
Log Population	0.007	0.006	0.009	0.009	0.003	0.087***	0.074***	0.098***	0.081***	0.080***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.023)	(0.016)	(0.016)	(0.018)	(0.016)	(0.016)
Average Wages	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.469***	-0.370***	-0.463***	-0.481***	-0.481***	-2.281***	-1.869***	-2.216***	-2.265***	-2.248***
	(0.148)	(0.135)	(0.148)	(0.152)	(0.156)	(0.182)	(0.144)	(0.175)	(0.179)	(0.174)
Observations	134,771	134,771	134,771	134,771	134,771	32,492	32,492	32,492	32,492	32,492
R^2	0.001	0.007	0.001	0.001	0.002	0.034	0.089	0.040	0.036	0.040

Notes: This table shows the results of a regression of counts of fatalities on indicators for the presence of a hazard in a given county/cluster. Counts of fatalities are aggregated to the county/cluster level. Fatalities data are sourced from SHELDUS, and run from 2000 through 2020.

Table IA.10: Differences in Property Damages by Hazard Type

	Counties					Clusters				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Drought	0.790**					2.215***				
	(0.317)					(0.247)				
Heat		0.559***					1.049***			
		(0.176)					(0.182)			
Wildfire			1.757***					2.036***		
			(0.151)					(0.115)		
Flooding				1.417***					1.129***	
				(0.0586)					(0.0376)	
Hurricane					3.142***					2.823***
					(0.212)					(0.301)
Log GDP	0.439***	0.443***	0.427***	0.412***	0.463***	0.603***	0.610***	0.581***	0.604***	0.615***
	(0.0600)	(0.0601)	(0.0594)	(0.0602)	(0.0590)	(0.0594)	(0.0594)	(0.0586)	(0.0588)	(0.0593)
Log Population	-0.267***	-0.274***	-0.258***	-0.241***	-0.297***	-0.0147	-0.0224	0.00402	-0.0478	-0.0268
	(0.0601)	(0.0602)	(0.0599)	(0.0594)	(0.0594)	(0.0577)	(0.0578)	(0.0575)	(0.0571)	(0.0576)
Average Wages	-0.0000776***	-0.0000780***	-0.0000767***	-0.0000789***	-0.0000767***	-0.000140***	-0.000143***	-0.000135***	-0.000145***	-0.000142***
	(0.0000163)	(0.0000164)	(0.0000155)	(0.0000173)	(0.0000156)	(0.0000197)	(0.0000197)	(0.0000192)	(0.0000194)	(0.0000196)
Observations	130538	130538	130538	130538	130538	31145	31145	31145	31145	31145
R^2	0.0160	0.0152	0.0222	0.0749	0.0492	0.185	0.182	0.197	0.212	0.187

Notes: This table shows the results of a regression of log property damages on indicators for the presence of a hazard in a given county/cluster, with controls included as regressors. Damages, as well as control variables, are aggregated to the county/cluster level. Property damages data are sourced from SHELDUS, and run from 2000 through 2020. Wages data are sourced from BEA. Population data are sourced from the US Census Bureau. Wages data are sourced from the QCEW.

Table IA.11: Differences in Crop Damages by Hazard Type

	Counties					Clusters				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Drought	0.806**					3.317***				
	(0.379)					(0.257)				
Heat		1.371**					0.636			
		(0.632)					(0.460)			
Wildfire			-0.062					0.541*		
			(0.308)					(0.313)		
Flooding				0.062					0.140	
				(0.226)					(0.160)	
Hurricane					4.066***					3.385***
					(0.532)					(0.738)
Log GDP	0.904***	0.948***	0.954***	0.957***	1.032***	3.292***	3.451***	3.443***	3.459***	3.424***
	(0.218)	(0.211)	(0.211)	(0.211)	(0.205)	(0.237)	(0.250)	(0.248)	(0.248)	(0.248)
Log Population	-1.209***	-1.251***	-1.252***	-1.254***	-1.361***	-2.940***	-3.048***	-3.037***	-3.055***	-3.042***
	(0.227)	(0.223)	(0.223)	(0.223)	(0.218)	(0.233)	(0.246)	(0.245)	(0.246)	(0.245)
Average Wages	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	11.264***	11.274***	11.212***	11.187***	11.091***	-2.897***	-3.624***	-3.649***	-3.699***	-3.384***
	(1.029)	(0.980)	(0.978)	(0.987)	(0.944)	(0.862)	(0.913)	(0.897)	(0.894)	(0.890)
Observations	14,220	14,220	14,220	14,220	14,220	3,040	3,040	3,040	3,040	3,040
R^2	0.054	0.044	0.043	0.043	0.089	0.178	0.112	0.112	0.111	0.122

Notes: This table shows the results of a regression of log crop damages on indicators for the presence of a hazard in a given county/cluster, with controls included as regressors. Damages, as well as control variables, are aggregated to the county/cluster level. Crop damages data are sourced from SHELDUS, and run from 2000 through 2020. Wages data are sourced from BEA. Population data are sourced from the US Census Bureau. Wages data are sourced from the QCEW.

Table IA.12: Differences in County-Level Damage Scaled by the Sample Median By Hazard Type

	Counties					Clusters				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Drought	0.583					-0.334				
	(0.365)					(0.235)				
Heat		-0.118					0.399***			
		(0.184)					(0.148)			
Wildfire			0.598***					0.737***		
			(0.152)					(0.120)		
Flooding				0.627***					0.606***	
				(0.062)					(0.039)	
Hurricane					1.157***					0.788**
					(0.230)					(0.343)
Log GDP	0.503***	0.517***	0.511***	0.505***	0.523***	0.801***	0.796***	0.785***	0.788***	0.798***
	(0.058)	(0.059)	(0.059)	(0.060)	(0.059)	(0.062)	(0.062)	(0.061)	(0.061)	(0.062)
Log Population	-0.393***	-0.410***	-0.405***	-0.399***	-0.419***	-0.320***	-0.320***	-0.310***	-0.329***	-0.320***
	(0.062)	(0.064)	(0.064)	(0.064)	(0.064)	(0.059)	(0.058)	(0.058)	(0.058)	(0.058)
Average Wages	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-3.329***	-3.322***	-3.297***	-3.391***	-3.342***	-8.519***	-8.456***	-8.424***	-8.359***	-8.474***
	(0.226)	(0.226)	(0.223)	(0.227)	(0.226)	(0.243)	(0.241)	(0.237)	(0.240)	(0.239)
Observations	134,771	134,771	134,771	134,771	134,771	29,667	29,667	29,667	29,667	29,667
R^2	0.014	0.012	0.013	0.025	0.017	0.137	0.137	0.139	0.148	0.137

Notes: This table shows the results of a regression of log of all (property and crop) damages, scaled by the sample median, for both county-level aggregates on indicators for the presence of a hazard in a given county/cluster along with an interaction of the damage indicator with the log of damage of that county's spatial cluster excluding that county. Damages are aggregated to the county/cluster level, and are in inflation-adjusted USD. Damages data are sourced from SHELDUS, and run from 2000 through 2020. Standard errors are double-clustered at the county- and month-level. *, **, and *** indicate 10%, 5%, and 1% significance, respectively.

Table IA.13: Differences in County-Level Damage Scaled by Hazard-Specific Medians By Hazard Type

	Counties					Clusters				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Drought	0.583					-0.334				
	(0.365)					(0.235)				
Heat		-0.118					0.399***			
		(0.184)					(0.148)			
Wildfire			0.598***					0.737***		
			(0.152)					(0.120)		
Flooding				0.627***					0.606***	
				(0.062)					(0.039)	
Hurricane					1.157***					0.788**
					(0.230)					(0.343)
Log GDP	0.503***	0.517***	0.511***	0.505***	0.523***	0.801***	0.796***	0.785***	0.788***	0.798***
	(0.058)	(0.059)	(0.059)	(0.060)	(0.059)	(0.062)	(0.062)	(0.061)	(0.061)	(0.062)
Log Population	-0.393***	-0.410***	-0.405***	-0.399***	-0.419***	-0.320***	-0.320***	-0.310***	-0.329***	-0.320***
	(0.062)	(0.064)	(0.064)	(0.064)	(0.064)	(0.059)	(0.058)	(0.058)	(0.058)	(0.058)
Average Wages	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-3.329***	-3.322***	-3.297***	-3.391***	-3.342***	-8.519***	-8.456***	-8.424***	-8.359***	-8.474***
	(0.226)	(0.226)	(0.223)	(0.227)	(0.226)	(0.243)	(0.241)	(0.237)	(0.240)	(0.239)
Observations	134,771	134,771	134,771	134,771	134,771	29,667	29,667	29,667	29,667	29,667
R^2	0.014	0.012	0.013	0.025	0.017	0.137	0.137	0.139	0.148	0.137

Notes: This table shows the results of a regression of log of all (property and crop) damages, scaled by the sum of hazard-specific medians for all hazards included in each cluster, for both county-level aggregates on indicators for the presence of a hazard in a given county/cluster along with an interaction of the damage indicator with the log of damage of that county's spatial cluster excluding that county. Damages are aggregated to the county/cluster level, and are in inflation-adjusted USD. Damages data are sourced from SHELDUS, and run from 2000 through 2020. Standard errors are double-clustered at the county- and month-level. *, **, and *** indicate 10%, 5%, and 1% significance, respectively.

Table IA.14: Differences in County-Level Damage By Cluster-level Damage Controlling for Cluster-Level Observables

	Counties									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Drought=1	-3.142***	-2.202**								
	(0.924)	(0.982)								
Drought=1 × Cluster Log Damage	0.260***	0.215***								
	(0.0655)	(0.0647)								
Heat=1			-0.481	-0.489						
			(0.686)	(0.669)						
Heat=1 × Cluster Log Damage			0.0851*	0.0728						
			(0.0480)	(0.0472)						
Wildfire=1					-0.659	-0.343				
					(0.466)	(0.486)				
Wildfire=1 × Cluster Log Damage					0.130***	0.110***				
					(0.0336)	(0.0354)				
Flooding=1							-0.0803	0.0224		
							(0.207)	(0.177)		
Flooding=1 × Cluster Log Damage							0.0603***	0.0608***		
							(0.0154)	(0.0132)		
Hurricane=1									0.534	0.699*
									(0.488)	(0.423)
Hurricane=1 × Cluster Log Damage									0.0226	0.00600
									(0.0268)	(0.0296)
Cluster Log Damage	0.532***	0.498***	0.552***	0.518***	0.548***	0.511***	0.517***	0.482***	0.542***	0.510***
	(0.0114)	(0.0108)	(0.0116)	(0.0112)	(0.0117)	(0.0114)	(0.0133)	(0.0131)	(0.0116)	(0.0116)
Log GDP	0.221***	-0.0130	0.246***	-0.00644	0.241***	0.00541	0.247***	0.00601	0.259***	-0.00384
	(0.0502)	(0.0809)	(0.0518)	(0.0832)	(0.0506)	(0.0833)	(0.0533)	(0.0857)	(0.0521)	(0.0830)
Average Wages	-0.0000430***	-0.0000468***	-0.0000446***	-0.0000423***	-0.0000443***	-0.0000455***	-0.0000469***	-0.0000425***	-0.0000452***	-0.0000405***
	(0.0000161)	(0.0000152)	(0.0000163)	(0.0000140)	(0.0000156)	(0.0000134)	(0.0000167)	(0.0000139)	(0.0000162)	(0.0000142)
Log Population	0.170***	-0.0117	0.136***	0.0382	0.138***	-0.0206	0.122**	0.0491	0.121**	0.0418
	(0.0501)	(0.208)	(0.0514)	(0.217)	(0.0505)	(0.215)	(0.0528)	(0.232)	(0.0517)	(0.216)
Cluster Log GDP	0.250***	-0.113	0.277***	-0.0977	0.279***	-0.0773	0.308***	-0.0831	0.277***	-0.107
	(0.0756)	(0.0711)	(0.0795)	(0.0728)	(0.0791)	(0.0725)	(0.0810)	(0.0712)	(0.0789)	(0.0739)
Cluster Average Wages	0.0000319*	0.000104***	0.0000378**	0.000107***	0.0000353**	0.000103***	0.0000266	0.000101***	0.0000392**	0.000108***
	(0.0000171)	(0.0000189)	(0.0000177)	(0.0000196)	(0.0000174)	(0.0000193)	(0.0000180)	(0.0000191)	(0.0000173)	(0.0000197)
Cluster Log Population	-0.833***	-0.429***	-0.878***	-0.463***	-0.872***	-0.473***	-0.882***	-0.453***	-0.872***	-0.449***
	(0.0770)	(0.0734)	(0.0811)	(0.0746)	(0.0809)	(0.0745)	(0.0825)	(0.0728)	(0.0808)	(0.0756)
County FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Date FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	91150	91112	91150	91112	91150	91112	91150	91112	91150	91112
R^2	0.330	0.414	0.319	0.405	0.323	0.408	0.338	0.425	0.322	0.406

Notes: This table shows the results of a regression of log of all (property and crop) damages for both county-level aggregates on indicators for the presence of a hazard in a given county/cluster along with an interaction of the damage indicator with the log of damage of that county's spatial cluster excluding that county. Damages are aggregated to the county/cluster level, and are in inflation-adjusted USD. Damages data are sourced from SHELDUS, and run from 2000 through 2020. Standard errors are double-clustered at the county- and month-level. *, **, and *** indicate 10%, 5%, and 1% significance, respectively.

Table IA.15: Differences in County-Level Property Damage By Cluster-level Damage

	Counties									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Drought=1	0.318	-0.162								
	(1.335)	(1.087)								
Drought=1 × Cluster Log Damage	0.008	0.023								
	(0.096)	(0.079)								
Heat=1			-0.082	-0.681						
			(0.680)	(0.641)						
Heat=1 × Cluster Log Damage			0.033	0.063						
			(0.045)	(0.040)						
Wildfire=1					-0.987	-0.461				
					(0.609)	(0.575)				
Wildfire=1 × Cluster Log Damage					0.199***	0.152***				
					(0.045)	(0.043)				
Flooding=1							-0.367**	-0.304*		
							(0.171)	(0.181)		
Flooding=1 × Cluster Log Damage							0.105***	0.097***		
							(0.012)	(0.013)		
Hurricane=1									-1.746***	-1.587***
									(0.655)	(0.515)
Hurricane=1 × Cluster Log Damage									0.185***	0.164***
									(0.033)	(0.033)
Cluster Log Damage	0.241***	0.256***	0.241***	0.256***	0.240***	0.254***	0.201***	0.218***	0.220***	0.238***
	(0.011)	(0.008)	(0.011)	(0.008)	(0.011)	(0.008)	(0.011)	(0.009)	(0.009)	(0.009)
Log GDP	0.561***	0.102	0.563***	0.102	0.548***	0.111	0.517***	0.108	0.569***	0.088
	(0.058)	(0.084)	(0.058)	(0.085)	(0.057)	(0.085)	(0.057)	(0.084)	(0.058)	(0.084)
Average Wages	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Population	-0.383***	-0.082	-0.387***	-0.077	-0.374***	-0.145	-0.339***	-0.105	-0.394***	-0.090
	(0.059)	(0.236)	(0.059)	(0.237)	(0.058)	(0.234)	(0.058)	(0.241)	(0.059)	(0.232)
Constant	2.854***	5.874**	2.871***	5.817**	2.926***	6.449***	3.342***	6.363***	3.122***	6.396***
	(0.293)	(2.427)	(0.292)	(2.436)	(0.284)	(2.398)	(0.280)	(2.418)	(0.274)	(2.385)
County FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Date FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	111,856	111,827	111,856	111,827	111,856	111,827	111,856	111,827	111,856	111,827
R^2	0.158	0.300	0.158	0.300	0.166	0.305	0.212	0.341	0.174	0.308

Notes: This table shows the results of a regression of log of property damages for both county-level aggregates on indicators for the presence of a hazard in a given county/cluster along with an interaction of log of the county-level damage with the log of damage of that county's spatial cluster excluding that county. Damages are aggregated to the county/cluster level, and are in inflation-adjusted USD. Damages data are sourced from SHELDUS, and run from 2000 through 2020. Standard errors are double-clustered at the county- and month-level. *, **, and *** indicate 10%, 5%, and 1% significance, respectively.

Table IA.16: Differences in County-Level Crop Damage By Cluster-level Damage

	Counties									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Drought=1	-4.764***	-2.126								
	(0.582)	(1.288)								
Drought=1 × Cluster Log Damage	0.332***	0.204***								
	(0.044)	(0.076)								
Heat=1			-5.174*	-6.180*						
			(2.751)	(3.386)						
Heat=1 × Cluster Log Damage			0.323*	0.355*						
			(0.180)	(0.207)						
Wildfire=1					0.040	-1.938				
					(1.392)	(1.652)				
Wildfire=1 × Cluster Log Damage					0.030	0.152				
					(0.104)	(0.113)				
Flooding=1							1.631***	0.358		
							(0.456)	(0.481)		
Flooding=1 × Cluster Log Damage							-0.117***	0.005		
							(0.033)	(0.035)		
Hurricane=1									-0.825	-2.030
									(1.436)	(1.515)
Hurricane=1 × Cluster Log Damage									0.117	0.145
									(0.086)	(0.091)
Cluster Log Damage	0.523***	0.419***	0.601***	0.471***	0.602***	0.471***	0.642***	0.469***	0.585***	0.464***
	(0.031)	(0.024)	(0.029)	(0.026)	(0.029)	(0.025)	(0.029)	(0.031)	(0.030)	(0.026)
Log GDP	0.508***	0.016	0.528***	-0.115	0.521***	-0.109	0.509***	-0.118	0.571***	-0.120
	(0.094)	(0.210)	(0.107)	(0.215)	(0.107)	(0.215)	(0.103)	(0.216)	(0.108)	(0.219)
Average Wages	-0.000***	0.000	-0.000**	0.000	-0.000**	0.000	-0.000**	0.000	-0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Population	-0.575***	-1.052	-0.632***	-1.041	-0.628***	-0.994	-0.606***	-0.975	-0.693***	-1.111
	(0.101)	(0.687)	(0.116)	(0.683)	(0.116)	(0.680)	(0.112)	(0.684)	(0.118)	(0.676)
Constant	2.363***	15.136**	1.542**	16.201**	1.558**	15.645**	0.949	15.469**	1.748**	17.047**
	(0.648)	(6.847)	(0.678)	(6.599)	(0.680)	(6.642)	(0.668)	(6.717)	(0.687)	(6.721)
County FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Date FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	12,367	11,775	12,367	11,775	12,367	11,775	12,367	11,775	12,367	11,775
R^2	0.546	0.746	0.518	0.737	0.518	0.737	0.522	0.739	0.524	0.738

Notes: This table shows the results of a regression of log of crop damages for both county-level aggregates on indicators for the presence of a hazard in a given county/cluster along with an interaction of the log of the county-level damage with the log of damage of that county's spatial cluster excluding that county. Damages are aggregated to the county/cluster level, and are in inflation-adjusted USD. Damages data are sourced from SHELDUS, and run from 2000 through 2020. Standard errors are double-clustered at the county- and month-level. *, **, and *** indicate 10%, 5%, and 1% significance, respectively.

Table IA.17: Differences in County-Level Injuries By Cluster-level Damage

	Counties									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Drought=1	0.066	0.018								
	(0.215)	(0.213)								
Drought=1 × Cluster Injuries	-0.000	-0.000								
	(0.000)	(0.000)								
Heat=1			7.712***	5.505***						
			(1.831)	(1.287)						
Heat=1 × Cluster Injuries			0.017	0.019						
			(0.013)	(0.013)						
Wildfire=1					1.586***	1.559***				
					(0.572)	(0.597)				
Wildfire=1 × Cluster Injuries					0.000	0.000				
					(0.002)	(0.002)				
Flooding=1							-0.153***	-0.169***		
							(0.044)	(0.036)		
Flooding=1 × Cluster Injuries							-0.001***	-0.001***		
							(0.000)	(0.000)		
Hurricane=1									-0.015	0.082
									(0.228)	(0.255)
Hurricane=1 × Cluster Injuries									0.007*	0.006
									(0.004)	(0.005)
Cluster Injuries	0.001***	0.001**	0.001***	0.000**	0.001***	0.001**	0.001***	0.001***	0.001***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log GDP	0.173***	0.048	0.132***	-0.005	0.155***	0.048	0.175***	0.049	0.174***	0.042
	(0.057)	(0.082)	(0.046)	(0.081)	(0.056)	(0.082)	(0.057)	(0.084)	(0.057)	(0.082)
Average Wages	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Population	0.032	-0.059	0.015	-0.066	0.047	-0.091	0.028	-0.062	0.030	-0.054
	(0.041)	(0.284)	(0.040)	(0.281)	(0.041)	(0.283)	(0.039)	(0.285)	(0.039)	(0.283)
Constant	-2.522***	0.315	-1.850***	1.065	-2.457***	0.658	-2.489***	0.373	-2.524***	0.347
	(0.577)	(2.784)	(0.406)	(2.721)	(0.564)	(2.789)	(0.569)	(2.775)	(0.574)	(2.778)
County FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Date FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	139,912	139,904	139,912	139,904	139,912	139,904	139,912	139,904	139,912	139,904
R^2	0.004	0.051	0.022	0.062	0.005	0.052	0.004	0.052	0.004	0.051

Notes: This table shows the results of a regression of injuries for both county-level aggregates on indicators for the presence of a hazard in a given county/cluster along with an interaction of the log of the county-level damage with the log of damage of that county's spatial cluster excluding that county. Injuries data are sourced from SHELDUS, and run from 2000 through 2020. Standard errors are double-clustered at the county- and month-level. *, **, and *** indicate 10%, 5%, and 1% significance, respectively.

Table IA.18: Differences in County-Level Fatalities By Cluster-level Damage

	Counties									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Drought=1	-0.018	-0.030**								
	(0.011)	(0.013)								
Drought=1 × Cluster Fatalities	-0.001***	-0.001***								
	(0.000)	(0.000)								
Heat=1			1.563***	1.376***						
			(0.281)	(0.223)						
Heat=1 × Cluster Fatalities			0.004	0.008						
			(0.013)	(0.013)						
Wildfire=1					0.179***	0.146**				
					(0.063)	(0.058)				
Wildfire=1 × Cluster Fatalities					0.001	0.001				
					(0.003)	(0.003)				
Flooding=1							0.020	0.018		
							(0.015)	(0.014)		
Flooding=1 × Cluster Fatalities							0.005	0.005		
							(0.003)	(0.003)		
Hurricane=1									0.263	0.227
									(0.206)	(0.175)
Hurricane=1 × Cluster Fatalities									0.003***	0.003***
									(0.000)	(0.000)
Cluster Fatalities	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.000	-0.000	0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Log GDP	0.046*	0.068	0.038	0.058	0.043	0.067	0.045*	0.072	0.045*	0.063
	(0.026)	(0.054)	(0.026)	(0.054)	(0.027)	(0.054)	(0.026)	(0.059)	(0.027)	(0.053)
Average Wages	-0.000	-0.000*	-0.000	-0.000	-0.000	-0.000*	-0.000	-0.000*	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Population	0.005	0.128*	0.002	0.115*	0.007	0.124*	0.007	0.124*	0.006	0.114
	(0.022)	(0.073)	(0.022)	(0.068)	(0.022)	(0.072)	(0.021)	(0.072)	(0.022)	(0.073)
Constant	-0.636***	-2.247**	-0.509***	-1.995*	-0.629***	-2.203**	-0.641***	-2.266**	-0.632***	-2.029**
	(0.166)	(1.112)	(0.149)	(1.078)	(0.166)	(1.106)	(0.166)	(1.146)	(0.167)	(0.953)
County FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Date FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	139,912	139,904	139,912	139,904	139,912	139,904	139,912	139,904	139,912	139,904
R^2	0.003	0.031	0.010	0.036	0.004	0.031	0.007	0.034	0.005	0.032

Notes: This table shows the results of a regression of fatalities for both county-level aggregates on indicators for the presence of a hazard in a given county/cluster along with an interaction of the log of the county-level damage with the log of damage of that county's spatial cluster excluding that county. Injuries data are sourced from SHELDUS, and run from 2000 through 2020. Standard errors are double-clustered at the county- and month-level. *, **, and *** indicate 10%, 5%, and 1% significance, respectively.

Table IA.19: Differences in County-Level Total Damages Scaled by the Sample Median By Cluster-level Damage

	Counties									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Drought=1	-5.807***	-3.875***								
	(1.169)	(0.990)								
Drought=1 × Cluster Log Damage	0.432***	0.318***								
	(0.080)	(0.065)								
Heat=1			0.286	-0.112						
			(0.744)	(0.654)						
Heat=1 × Cluster Log Damage			0.022	0.035						
			(0.050)	(0.043)						
Wildfire=1					-1.058	-0.624				
					(0.657)	(0.608)				
Wildfire=1 × Cluster Log Damage					0.200***	0.157***				
					(0.048)	(0.044)				
Flooding=1							-0.168	-0.150		
							(0.182)	(0.184)		
Flooding=1 × Cluster Log Damage							0.091***	0.087***		
							(0.013)	(0.013)		
Hurricane=1									-1.743***	-1.603***
									(0.633)	(0.555)
Hurricane=1 × Cluster Log Damage									0.182***	0.161***
									(0.032)	(0.035)
Cluster Log Damage	0.248***	0.262***	0.262***	0.274***	0.261***	0.272***	0.227***	0.240***	0.243***	0.257***
	(0.011)	(0.008)	(0.011)	(0.009)	(0.011)	(0.009)	(0.012)	(0.010)	(0.010)	(0.009)
Log GDP	0.644***	0.070	0.696***	0.069	0.682***	0.081	0.664***	0.072	0.708***	0.056
	(0.061)	(0.086)	(0.066)	(0.090)	(0.065)	(0.090)	(0.066)	(0.091)	(0.066)	(0.090)
Average Wages	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Population	-0.511***	-0.128	-0.583***	-0.088	-0.569***	-0.152	-0.549***	-0.102	-0.595***	-0.099
	(0.065)	(0.244)	(0.071)	(0.257)	(0.070)	(0.256)	(0.071)	(0.265)	(0.071)	(0.250)
Constant	-6.902***	-3.107	-7.039***	-3.700	-6.997***	-3.150	-6.650***	-3.325	-6.818***	-3.181
	(0.296)	(2.474)	(0.301)	(2.525)	(0.293)	(2.500)	(0.297)	(2.537)	(0.288)	(2.460)
County FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Date FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	115,739	115,712	115,739	115,712	115,739	115,712	115,739	115,712	115,739	115,712
R^2	0.187	0.336	0.169	0.325	0.176	0.330	0.216	0.361	0.183	0.332

Notes: This table shows the results of a regression of log of total damages scaled by the sample median for both county-level aggregates on indicators for the presence of a hazard in a given county/cluster along with an interaction of the log of the county-level damage with the log of damage of that county's spatial cluster excluding that county. Damages are aggregated to the county/cluster level, and are in inflation-adjusted USD. Damages data are sourced from SHELDUS, and run from 2000 through 2020. Standard errors are double-clustered at the county- and month-level. *, **, and *** indicate 10%, 5%, and 1% significance, respectively.

Table IA.20: Differences in County-Level Total Damages Scaled by Hazard-Specific Medians By Cluster-level Damage

	Counties									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Drought=1	-6.851***	-2.533***								
	(1.213)	(0.874)								
Drought=1 × Cluster Log Damage	0.392***	0.170***								
	(0.084)	(0.054)								
Heat=1			-0.038	-0.256						
			(1.277)	(1.106)						
Heat=1 × Cluster Log Damage			0.029	0.023						
			(0.082)	(0.068)						
Wildfire=1					-0.719	-1.358**				
					(0.710)	(0.615)				
Wildfire=1 × Cluster Log Damage					0.102**	0.123***				
					(0.051)	(0.043)				
Flooding=1							2.309***	1.197***		
							(0.612)	(0.435)		
Flooding=1 × Cluster Log Damage							-0.105***	-0.043		
							(0.040)	(0.030)		
Hurricane=1									-2.776***	-4.258***
									(0.669)	(0.700)
Hurricane=1 × Cluster Log Damage									0.088**	0.134***
									(0.035)	(0.038)
Cluster Log Damage	0.293***	0.291***	0.327***	0.306***	0.328***	0.302***	0.411***	0.344***	0.342***	0.313***
	(0.012)	(0.011)	(0.014)	(0.011)	(0.014)	(0.011)	(0.038)	(0.027)	(0.016)	(0.012)
Log GDP	0.613***	-0.139	0.632***	-0.172	0.616***	-0.155	0.668***	-0.185	0.602***	-0.169
	(0.092)	(0.150)	(0.115)	(0.154)	(0.115)	(0.155)	(0.109)	(0.154)	(0.114)	(0.151)
Average Wages	-0.000***	-0.000	-0.000***	-0.000	-0.000***	-0.000	-0.000***	-0.000	-0.000***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Population	-0.414***	0.493	-0.445***	0.577	-0.432***	0.529	-0.484***	0.644	-0.400***	0.601
	(0.098)	(0.412)	(0.124)	(0.432)	(0.124)	(0.428)	(0.118)	(0.444)	(0.123)	(0.436)
Constant	-8.582***	-7.675*	-9.141***	-8.341*	-9.103***	-8.037*	-11.074***	-9.891**	-9.350***	-8.602*
	(0.406)	(4.302)	(0.451)	(4.388)	(0.444)	(4.323)	(0.671)	(4.452)	(0.477)	(4.378)
County FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Date FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	29,361	29,117	29,361	29,117	29,361	29,117	29,361	29,117	29,361	29,117
R^2	0.259	0.473	0.232	0.469	0.236	0.471	0.242	0.472	0.243	0.482

Notes: This table shows the results of a regression of log of total damages scaled by the sum of all hazard-specific medians for all hazards included in each cluster, for both county-level aggregates on indicators for the presence of a hazard in a given county/cluster along with an interaction of the log of the county-level damage with the log of damage of that county's spatial cluster excluding that county. Damages are aggregated to the county/cluster level, and are in inflation-adjusted USD. Damages data are sourced from SHELDUS, and run from 2000 through 2020. Standard errors are double-clustered at the county- and month-level. *, **, and *** indicate 10%, 5%, and 1% significance, respectively.