# Compounding in Natural Disaster Damages

Jacob Kim-Sherman*
University of California, Berkeley

Lee Seltzer
Federal Reserve Bank of New York

**Abstract**

Finance research on natural disasters often relies on panel regressions of different outcomes on disaster damages, where contrary to environmental science research, SUTVA is assumed. We introduce a method to identify spatial clusters in natural disaster damages datasets, and consistent with compounding effects of natural disasters, show that counties tend to experience 0.26% more damage for each additional 1% of damage measured at the disaster cluster-level. We also find that house price returns typically decline by 20 bps after a hurricane, while an analysis excluding cluster-level damage predicts a marginal increase in house price returns. This highlights that ignoring natural disaster compounding can drastically alter the conclusions of empirical research.
**Keywords:** Natural Disasters, Compound disaster risk

**JEL Codes:** Q50, Q54

*Contact: lee.seltzer@ny.frb.org. This paper previously circulated as "Clustering in Natural Disaster Losses" and "Clustering in Natural Disaster Damages." The authors thank Tobias Berg, Daniel Streitz, Tim Park, Hyeyoon Jung, Viral Acharya, Julian Di Giovanni, Matteo Crosignani, Martin Hiti, Jose-Luis Cruz, Zack Liu, Ben Dennis (discussant), Joachim Weill (discussant), Shikhar Singla (discussant) and seminar participants at the Federal Reserve Bank of New York, the Federal Reserve System Regional and Energy Meetings, the Texas Finance PhD Alumni Conference and the 2026 Eastern Finance Association Annual Meeting for useful comments and discussion. Jessica Chen provided excellent research assistance. The views expressed herein are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of New York or the Federal Reserve System.

# 1 Introduction

In September 2024, Hurricane Helene struck the United States, triggering Federal Emergency Management Agency (FEMA) disaster declarations across five states (Alabama, Florida, Georgia, North Carolina, and South Carolina). CoreLogic estimated that the disaster caused $47.5 billion in damage, including $20–$30 billion in uninsured flood losses.[1] It is possible that the long-run effects of the disaster may have been more severe since it affected such a large region. For instance, since disaster relief resources are finite at the local level, a county may receive less aid in cases where their neighbors are affected by the same disaster, such as in Hurricane Helene. In this paper, we propose a framework to capture how the effects of disasters may be correlated across space in empirical finance and economics research.

Use of natural disaster data has become increasingly common in empirical economics and finance. For instance, Table 1 lists the existing 37 papers published in the top 6 finance journals using data on natural disasters as of March, 2026.[2] In previous work in empirical economics and finance, most research on natural disasters has utilized county-by-month-level data to run panel regressions of different economic outcomes on disaster damages.[3] The regressions often make use of county and time fixed effects while clustering standard errors at the county-level. Making the Stable Unit Treatment Value Assumption (SUTVA) is necessary to interpret these regressions, which in this context requires that disaster damages

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

[2] The top finance journals are defined as *Journal of Finance*, *Journal of Financial Economics*, *Journal of Financial and Quantitative Analysis*, *Management Science*, *Review of Finance*, and *Review of Financial Studies*.

[3] 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); Hasan et al. (2024).

for a county at a given point in time are uncorrelated with disaster damages in other counties and at other time periods. On the other hand, the climate science literature finds consistent evidence that natural disaster occurrences are correlated over space, where disasters tend to be concentrated in certain regions.[4] Given this additional context from the climate science literature, the tendency of disaster damages to be spatially correlated could pose a threat to important assumptions typically made in empirical research. This paper integrates this potential correlation in the occurrence of natural disasters into the finance literature. We then examine potential amplification effects induced by this correlation, which we refer to as "*compounding*" of natural disaster damages.

Compounding related to natural disasters 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 contemporaneous disasters. In these circumstances, outcomes from natural disasters could be correlated across counties, thereby introducing frictions to insurance markets for housing and other assets vulnerable to disaster damages. This could lead compounding of natural disasters to have financial stability implications, making it important for researchers, policymakers and financial market participants to consider. To allow researchers to analyze these effects, this paper develops algorithmic approaches to identify groups of counties experiencing common natural disasters at the same time, which we refer to as "*spatial clusters*" of natural disasters. Importantly, while existing classifications, such as FEMA emergency and disaster declarations, can be used to identify named storms such as hurricanes, to our knowledge this is the first

[4]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)).

systematic approach researchers can use to identify group of smaller disasters, such as thunderstorms. We hypothesize that compounding of natural disaster damage is likely to occur between counties located in the same spatial cluster.

Given its status as the most widely used data on natural disaster damages in finance research, our analysis utilizes the Spatial Hazards Events and Losses Database for the United States (SHELDUS). SHELDUS has been used in more than half of the published papers listed in Table 1, and continues to be used in working papers circulating among researchers. However, the method in this paper is useful for any source of natural disaster data. In fact, we also provide results using the Losses from Natural Disasters Data (LND) from Crosignani and Hiti (2025) in Appendix IA.D, and the results are similar.

Our analyses reveal three key facts about compounding of natural disaster damages within spatial disaster clusters. 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. In particular, the average logged damage for all clusters in the 60th percentile of damages and below is about 10 ($22 million). This is because there is little variation in the disaster 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 the average logged damage for the 95th percentile bin reaches about 15 ($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.

Second, we find that certain hazard types appear more severe when examining a disaster-

cluster level dataset than when using county-by-month-level data. Specifically, when examining summary statistics according to hazard type in county-level data, drought is the ninth most severe hazard type. However, similar summary statistics aggregated to the spatial cluster-level reveals drought to be the second most severe hazard type. This illustrates that analyzing natural disasters at the county-level may have led researchers to understudy certain hazard types.

We then consider whether there exists a correlation between damages for different counties, contained in the sample spatial disaster cluster. To this end, we adapt the empirical model from Berg et al. (2021) to the natural disaster setting to examine whether we observe within-spatial cluster compounding when examining natural disasters. Consistent with the existence of within-spatial cluster compounding, we find that county-level damages tend to be larger when the county is part of a cluster that experiences more damage. A county typically experiences about 0.26% more disaster damage for each additional 1% of damage measured at the cluster-level. We also find that this result is especially acute for certain hazard types, such as floods, hurricanes and wildfires. The finding that county-level damages are larger when the rest of the cluster experiences more damage suggests that the tendency for natural disasters to be regionally-concentrated is associated with the compounding of disaster damages.

Lastly, we consider the economic implications of the compound effects of natural disaster damages by conducting an analysis of how house price returns change following hurricanes. We find that using the standard approach of regressing house price returns on hurricane damage, house price returns are expected to increase by 50 bps for every billion dollars in hurricane damage. However, using the spatial-cluster level damage to incorporate com-

pounding into the analysis reveals that the effect of hurricane damage on house price returns is ambigiuous, and varies based on the size of the cluster. A back-of-the-envelope calculation shows that without considering compounding, the average hurricane can be expected to lead to a 5.5 bp decline in house price returns. However, a similar calculation which incorporates the effects of natural disaster compounding predicts a 20 bp decline in house price returns following the average hurricane. That is, failing to account for compounding natural disasters could lead researchers to mistakenly believe that hurricanes act as fiscal stimulus for counties.

To summarize, this paper introduces a method to identify natural disaster clusters, thereby integrating spatial correlation in the occurrence of natural disasters into empirical research in economics and finance. In doing so, we provide a tool for economists to bring their analyses on natural disasters more in line with the findings from the climate science literature. We show that incorporating compounding into analyses increases the estimated severity of the most severe natural disasters, as well as the estimated severity of certain hazard types such as droughts. We also confirm that county-level disaster damages are higher when the rest of the disaster cluster also experiences higher damages. Lastly, we show that in the context of housing price returns, failing to account for compounding could bias regression estimates. These findings indicate that understanding natural disaster compounding is deeply important for conducting analysis related to natural disasters.

In doing so, we provide a valuable contribution to the literature in finance on how climate risks affect financial markets. Finance papers often use data on natural disaster damages in their empirical analyses. These data have been used to study varied questions such as how exposure to disasters affect household financial behavior (Heimer et al., 2019), how financing

constraints affect firm product market behavior (Ge, 2022), and how bank lending responds to natural disasters (Cortés and Strahan, 2017; Lim and Nguyen, 2021).

Existing work often addresses correlated error terms by clustering standard errors at the county or state level (Cameron and Miller, 2015). Moreover, regression analysis typically includes county and month fixed effects to address potential spatial and temporal correlation. However, these approaches may be insufficient for at least two important reasons. First, if there exist a correlation between damages in disaster counties, regression estimates examining changes in county-level outcomes after disasters may be biased due to a violation of SUTVA (Berg et al., 2021). To our knowledge, we provide the first method to identify individual disaster clusters which can be used to examine disaster damages in a manner consistent with how environmental scientists think about disasters. Second, we expect error terms may be correlated within spatial and temporal clusters. While researchers typically cluster standard errors at the county or state level, natural disasters typically do not respect geopolitical boundaries.

Our paper proceeds as follows. In section 2, we discuss the data and introduce our algorithm to identify natural disaster clusters. In section 3, we provide a descriptive analysis examining cluster-level disaster damage. In section 4, we apply the data on natural disaster clusters to examine whether the response to housing price returns to hurricane damage may be compounded within disaster clusters. In section 5, we use the regression estimates from section 4 to provide a back-of-the-envelope calculation of how house price returns can be expected to change after the typical hurricane. In section 6, we conclude and discuss the policy implications of this research.

# 2 Data and Methodology

## 2.1 Data

The primary dataset 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.[5] While we focus on SHELDUS, as it is the most widely used dataset on natural disasters in economic research, this approach could be easily adapted for any other type of data on negative outcomes experienced due to natural disasters by individuals, firms or municipalities.

Although we use SHELDUS given its prevalence in the finance literature, we acknowledge several limitations of the SHELDUS data. In particular, SHELDUS allocates damages uniformly across disaster-affected counties (Tran et al., 2020; Crosignani and Hiti, 2025). To some extent, aggregating to the level of a spatial natural disaster cluster could potentially alleviate concerns related to the uniform losses assumption. However, to ensure this concern is not driving the effects documented in this paper, Appendix IA.D includes a replication of our results using the Losses from Natural Disasters (LND) data from Crosignani and Hiti (2025), which instead allocates damages according to economic activity in the region. Specifically, Crosignani and Hiti (2025) allocates disaster damages according to area, employment, income, housing and population, in addition to an equal-weighting scheme similar to that used in SHELDUS. The results are broadly similar to those observed in the main analysis,

[5] 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.

highlighting that the methods in this paper are useful for any data on natural disasters.

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

## 2.2 Methodology to Identify Natural Disaster Clusters

Regression analysis of natural disasters requires assuming SUTVA, which states that adverse effects of natural disasters for a given county at a given time are independent of effects of disasters in other counties and times.[6] However, the climate science literature presents several important challenges to such an assumption.[7] Some counties may be unconditionally more likely to experience certain types of disasters than others. 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 simultaneity could potentially exacerbate the strain on economic resources for each individual county. These challenges to SUTVA motivate the development of a method 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

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

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

propose the following approaches for identifying common patterns of disasters in county-by-month-level data.

### 2.2.1 Identifying Spatial Clusters of Disasters

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, 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 they are geographically contiguous and have at least one common hazard:

$$PCCP(i, j) = 1 \text{ if counties } i \text{ and } j \text{ are adjacent and}$$

$$H_t^i \cap H_t^j \neq \emptyset.$$

where $H_t^i$ and $H_t^j$ are defined as above. Consider the example of two neighboring Texas counties, Harris and Montgomery, which were both hit by hurricane, wind and flooding events in August 2017. Since Harris and Montgomery are adjacent, and $H_{2017m8}^{\text{Harris, TX}} \cap H_{2017m8}^{\text{Montgomery, TX}} = \{$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 a distance of $n$ 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, following the inductive process until no more proximate common climate patterns can be identified.

As an example, Figure 1 applies the spatial cluster algorithm to the case of Hurricane Harvey. Panel (a) displays the spatial cluster associated with Hurricane Harvey, while panel (b) shows all counties which were included in the Presidential Disaster Declaration for Hurricane Harvey. The spatial cluster identified by our algorithm closely aligns with the Hurricane Harvey Presidential Disaster Declaration. Most discrepancies arise from counties where a presidential disaster was declared, but ultimately, zero damages were reported.[8] Figure IA.D.1 shows the corresponding spatial cluster using the LND data from Crosignani and Hiti (2025), which is identical to the cluster generated from SHELDUS, highlighting that this approach can be useful when examining any natural disaster dataset.

[8]Comparing the 63 counties identified by the cluster-identification algorithm in this spatial cluster to the 75 counties identified in a Presidential Disaster Declaration (PDD) in August 2017 with the name "Harvey", we find an intersection of 60 counties (80% of the counties identified in the PDD). All of the 15 counties (the remaining 20%) identified in the PDD that are not a part of the cluster report zero damages in the SHELDUS dataset. Of these, three highly populated counties that did not experience damage (Dallas, Tarrant, and Travis) were added by Governor Abbott because they were sheltering a significant number of evacuees.

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

Summary statistics on disasters, using both data at the spatial cluster-level and at the county-level, are displayed in Table 2. The size of the average spatial cluster is about 4 counties, and total damage is $17.5 million on average. On the other hand, the median total damage is only $23,600, indicating that the distribution is positively skewed.[9] The total damage numbers include both property and crop damages, although property damages contribute to 90% of the total damage. All results in the main text are based on total damages, although results for specific damage types are included in Internet Appendix IA.E.[10]

### 2.2.2 Identifying Temporal and Spatiotemporal Clusters

Much of the conceptual framework developed for identifying spatial clusters can also be used to identify clusters across time (i.e., temporal clusters). 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:

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

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

[10]Note that by construction, the spatial 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. Appendix IA.C also includes a version of the regression analyses with an adjustment for the number of county-hazards experienced in a given cluster.

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 Figure IA.E.4, alongside the temporal evolution of this cluster in Figure IA.E.5. Note that the results in the main text will focus on spatial clusters, although the Internet Appendix contains analogous results for spatiotemporal clusters. Without loss of generality, we hereafter use the term "clusters" to refer to spatial clusters of natural disasters.

This section has provided a description of our new approach to identifying clusters of natural disasters using data on natural disaster damages. In the next section, we will provide a descriptive analysis of disaster damages calculated based on a cluster-level dataset.

# 3 Comparing Cluster- and County-Level Damages

In the previous section, we introduced our algorithm to identify clusters. 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.

## 3.1 Exploring distributions of disaster damage

To visualize the distributions of damage according to the type of data 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 that of the county-level distribution.[11] Figure IA.D.2 shows similar histograms generated using the LND data from Crosignani and Hiti (2025). All appear similar to the result shown in the main text.

The histograms show that the clusters with the most damage tend to have more extreme values than the counties with the most damage. One potential explanation for this could be that disasters covering 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, as all clusters up until this point only have one county. However, disaster damage increases beyond this point, eventually reaching an 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.[12] Figures IA.E.6 and IA.E.7 display histograms and binscatter plots using property and crop damages, and Figure IA.E.8 display histograms and binscatter plots using spatiotemporal clusters. All appear similar to the main set of results.

To study the differences in disaster distributions according to the type of hazard observed,

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

[12] Binscatter plots using the LND data from Crosignani and Hiti (2025) are displayed in Figure IA.D.3, and results are similar.

we next examine detailed summary statistics by the type of hazard. Table 3 displays the distribution of disaster damages according to hazard type when using county-level data. Perhaps unsurprisingly, hurricanes are the most damaging hazard in the data, followed by earthquakes. Table 4 displays similar information using cluster-level data. Droughts are the second-most damaging hazard type on average in the cluster-level data, as opposed to only the ninth most damaging in the county-level dataset. This is likely driven by the fact that in terms of the number of counties, droughts tend to occur in the form of the largest clusters. This observation underscores the notion that county-level data may especially understate damages in the case of hazards that take the form of especially large spatial clusters. Similar summary statistics for spatiotemporal clusters are shown in Table IA.E.2.

We also examine the components of damages observed in SHELDUS by displaying separate summary statistics by hazard type on property and crop damages. County-level statistics are displayed in Table 5, and spatial cluster-level statistics are displayed in Table 6. Consistent with the summary statistics in Table 2, property damages are much larger than crop damages. Interestingly, drought is the hazard type with the greatest crop damages, and droughts also appear much more severe when examining disaster clusters.

In this subsection, we have shown that important differences exist 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 evidence indicating 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.

## 3.2 Relationship Between County- and Cluster-Level Damage

Distributions using cluster-level data appear more skewed than when using county-level data, and natural disasters affecting more counties tend to yield higher damages. These patterns may be driven by "compounding" of disaster damage, where compounding is defined as amplification effects of county-level disaster damage within natural disaster clusters. In particular, counties may experience greater adverse effects of natural disasters if neighboring counties are experiencing the same disaster. For instance, if a county experiences a disaster at the same time that nearby counties face disasters, both counties may be worse prepared to respond to the disaster due to strained resources to mitigate the damages, or greater degradation of shared infrastructure between the counties. As a result, each county may experience more damage than the counterfactual scenario where the disaster only affects a single county. In this subsection, we employ a regression analysis to test the hypothesis that there exists within-cluster compounding of natural disaster damages by examining whether counties belonging to clusters with greater disaster damage tend to experience more damage.

To do this, we adapt the methodology introduced in Berg et al. (2021) to study spillover effects in empirical corporate finance:

$$y_{ig} = \beta_0 + \beta_1 d_{ig} + \beta_T \bar{d}_g d_{ig} + \beta_C \bar{d}_g (1 - d_{ig}) + \epsilon_{ig}, \tag{1}$$

where $y_{ig}$ is an outcome variable for unit $i$ in group $g$, $d_{ig}$ is one if unit $i$ in group $g$ is treated, and $\bar{d}_g$ is the percentage of group $g$ that is treated. The group is some set of

observations, that are connected in such a way that one may expect to observe spillover affects between then. For example, a corporate finance researcher studying the effects of natural disasters on establishment-level employment may expect to observe spillover effects between establishments owned by the same firm, so in this case $g$ would be the firm. In this sense, $\beta_T$ captures the spillover effect of a treatment on treated units. Note that fixed effects are excluded from this specification, as Berg et al. (2021) and Chudik et al. (2025) show that fixed effects can exacerbate bias related to spillover effects. Nonetheless, we provide results in the appendix using fixed effects. We adapt this approach to a simple-difference setting, examining the compounding of natural disaster damages:[13]

$$log(D_{i,t}) = \beta_1 log(D_{j,t}^{-i}) + \Gamma X_{i,t} + \epsilon_{i,t}, \tag{2}$$

where $log(D_{i,t})$ is the log of the damage of county $i$, at time $t$, and $log(\bar{D}_{j,t}^{-i})$ is the log of the damage of cluster $j$ (excluding damage for county $i$) at time $t$. $X_{i,t}$ 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. $\beta_1$ is analogous to $\beta_T$ in the Berg et al. (2021) setting, where $\beta_1 > 0$ is consistent with counties experiencing compounding of natural disaster damage.

One noteworthy feature of the case of natural disasters is that $g$, the group of counties we expect to see correlated outcomes between, is the disaster region itself. Natural disasters therefore potentially provides a unique case where outcomes can become endogenously

[13]Since disaster damages are only available conditional on a disaster occurring, we are required to examine this question in a simple-difference setting.

correlated due to the presence of a common treatment. In essence, this test is a first step in understanding whether this endogenous correlation between treated outcomes occurs. In some sense, we can think of "natural disaster compounding" as essentially spillover effects related to natural disasters, occurring within an endogenously region affected by the disaster.

Results for this regression are shown in column (1) of Table 7. Consistent with compounding of natural disaster damage, $\beta_1$ is equal to about 0.26, meaning that a 1% increase in cluster-level damage is associated with a 0.26% increase in county-level damage. Therefore, the effects of natural disasters on a county appear more severe when the disaster also affects neighboring counties. To examine whether these results are robust to using alternative natural disasters data, Table IA.D.1 shows this regression using the LND data from Crosignani and Hiti (2025). Under all potential weighting schemes, greater disaster damage at the cluster-level is associated with more damage at the county-level.

The previous summary statistics showed that some hazard types appear more severe when analyzing them in cluster-level data. We ask, analogously, whether natural disaster compounding is more apparent for some hazard types than for others. To test this hypothesis, we include hazard type indicator variables, and their interactions with the cluster-level disaster damages in columns (2) through (6). We explore damages related to droughts, heat, wildfires, floods and hurricanes. Higher cluster-level damage is associated with more county-level damage for all five of the explored hazard types except for heat.

The results in this subsection are robust to alternative specifications. For instance, in Appendix IA.C, we apply a rescaling procedure to calculate the damages used in regressions to adjust for the fact that cluster-level damages are mechanically larger if a disaster affects more counties. We also produce these results separately examining property damages in

Table IA.E.3 and crop damages in Table IA.E.4. Both of these tests produce similar results to when examining total damages. Additionally, while Berg et al. (2021) advises against using fixed effects in this test, we display versions of this test that include both county and time fixed effects, as well as county and state-by-time fixed effects in Table IA.E.5 and Table IA.E.6. In both cases, the general conclusion of the results are unchanged.

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. This finding is consistent with counties experiencing compounding of natural disaster damages within clusters. At the same time, the results in this section show that some hazard types appear more severe after incorporating compounding into an analysis.

While the findings in this section show that counties face greater damages from natural disasters when neighboring counties also face the same disaster, they do not speak to the economic implications of natural disaster compounding. In the next section, we examine how cluster-level damages can interact with the effects of natural disasters on housing markets.

# 4 Housing price returns and cluster-level spillovers

The results in section 3 provide evidence that there are compound effects of natural disaster damages. However, what are the implications for outcomes of interest to economists? To this end, we now study how the occurrence of natural disasters affects outcomes related to housing price returns. We then conduct several analyses to understand both how the point estimates and standard errors may be affected by the presence of natural disaster compounding. The procedure used in this section can also provide a roadmap for researchers

trying to understand how compounding may affect other economic variables of interest.

We continue using the approach in the spirit of Berg et al. (2021) to test whether compounding of adverse outcomes from natural disasters occurs within natural disaster regions. Specifically, we first implement the following regression to examine how housing markets in counties change following the incidence of a natural disaster:

$$HPReturns_{it} = \beta Damage_{i(t-11,t)} + \Gamma X_{it} + FE + \epsilon_{it}, \tag{3}$$

where $Damage_{i(t-11,t)}$ is the total disaster damage for county $i$ in the year leading up to month $t$ in billions of dollars and $X_{it}$ are county-by-time level controls (the natural log of county GDP, wages and the natural log of population). In order to focus on especially severe natural disasters, we study damages related to hurricanes. We obtain information on housing prices from the Zillow Home Values Index (ZHVI). Using the ZHVI, we calculate house price returns as year-over-year changes in house prices within a county.

Next, we run the following regression to study whether housing markets change differentially with cluster-level damage, and whether that effect interacts with county-level natural disaster damages:

$$\begin{aligned} HPReturns_{it} = {} & \beta_1 Damage_{i(t-11,t)} + \beta_2 Damage^{-i}_{(t-11,t)} + \beta_3 Damage_{i(t-11,t)} \times Damage^{-i}_{(t-11,t)} \\ & + \Gamma X_{it} + FE + \epsilon_{it}, \end{aligned} \tag{4}$$

where $Damage^{-i}_{(t-11,t)}$ is the rest-of-cluster hurricane damage for the disaster cluster containing county $i$ in the year preceding time $t$ in billions of dollars. We obtain this value by taking

the average of the rest-of-cluster hurricane damage for county $i$ in the year preceding month $t$, and multiplying it by 12.[14]

While this analysis reveals how county-level damages on housing market outcomes may be compounded within disaster-clusters, it does not necessarily resolve issues related to the calculation of standard errors. To this end, we also include an estimation of Equation 3 using Conley (1999) standard errors. Conley (1999) standard errors arbitrarily assign clusters according to spatial autocorrelation, and for this reason should address any concerns about spatial autocorrelation of error terms related to the tendency for natural disasters to occur in clusters across space.

Results for the analysis are included in Table 8. Column (1) shows simple regressions of year-over-year changes in house price returns on disaster damage. For every billion dollars of disaster damage in a county, house price returns tend to increase by 1.1 percentage points. This is consistent with previous findings in the literature that house prices tend to increase following natural disasters (Roth Tran and Wilson, 2025). Column (2) include county and month fixed effects, where the effect reduces to about 0.5 percentage points.

Next, we estimate the regression from Equation 4 to understand how house price returns are affected by compounding related to rest-of-cluster hurricane damage. These results are shown in column (3). First, note that when controlling for the rest-of-cluster hurricane damage, the base effect of hurricane damage on house price returns is larger. Specifically, a one billion dollar increase in hurricane damage is now associated with a 1.6 percentage point increase in house price returns. However, examining the estimate of $\beta_3$ is informative of how

[14]Since we are examining compounding of disasters within a natural disaster region, $\bar{d}_{ig}$ in Equation 1 always equals zero.

county-level hurricane damage interacts with cluster-level hurricane damage. We find that this increase in house price returns is somewhat muted by rest-of-cluster damage. When we include county and month fixed effects in the regression, this effect becomes even more clear. In particular, if a county experiences one billion dollars of hurricane damage, and zero rest-of-cluster damage, we can expect to observe a 50 bp percentage point increase in house prices. However, this effect is attenuated as the size of the cluster increases.

Lastly, we study whether standard errors appear to be affected by spatial autocorrelation in natural disaster damages by using Conley (1999) standard error calculations in columns (5) and (6). The standard errors are not greatly changed by use of Conley (1999) standard errors, and in fact are sometimes smaller than when double-clustering at the county and month levels.

One may worry that the results in this section could be driven by skewness in natural disaster damages. We address this concern by implementing a version of this regression using the natural log of 1 plus damages in Table IA.E.7. We also provide a version of this analysis using damages rescaled by according to the severity of the median hazard's damage in Appendix IA.C. In both cases, the results are broadly similar to those discussed in this section.

These results show that accounting for rest-of-cluster damage can have meaningful effects on the estimates produced in regression analysis. At the same time, accounting for spatial autocorrelation in the construction of standard errors does not have a substantial effect on inference. In the context of housing price returns, we can therefore conclude that while compounding of natural disaster damages may bias regression estimates, it does not present issues for the calculation of standard errors. In the next section, we provide a back-of-the-

envelope calculation of the bias introduced by failing to account for compounding in the housing market setting, and discuss the implication of these findings for researchers.

# 5 Quantifying the effect of natural disaster compounding for housing markets

Next, we use the summary statistics on county- and cluster-level natural disaster damages introduced in section 3 to provide a back-of-the-envelope calculation of how researchers may evaluate the effects of the average hurricane on house price returns differently when compounding is taken into account.

According to Table 3, the average hurricane results in $116.4 million in county-level damage. Based on the regression results in column (2) of panel (a), which use county and month fixed effects, the average hurricane leads to $0.5\% \times .1164 = 0.058\%$ increase in housing price returns. Next, we examine the estimates when taking into account cluster-level damages. According to the cluster-level summary statistics in Table 4, the average hurricane is associated with $1.515 billion in hurricane damage, meaning the average county experiences $\$1.515bn - \$0.1164bn = \$1.3986bn$ of rest-of-cluster damage. This means that when accounting for potential compounding associated with rest-of-cluster hurricane damage, we should be able to calculate the change in house price returns following the average hurricane as:

$$
\begin{aligned}
\Delta HPReturns = \beta_1 \times \text{Average county damage} + \beta_2 \times \text{Average rest-of-cluster damage},& \\
+ \beta_3 \times (\text{Average county damage} \times \text{Average rest-of-cluster damage}),& \\
= 1.1\% \times 0.1164 - .2\% \times 1.3986 - 0.3\% \times (0.1164 \times 1.3986),& \\
= 0.128\% - 0.280\% - 0.048\%,& \\
= -0.2\%.&
\end{aligned}
$$

Therefore, without accounting for compounding, we would have assessed the average hurricane as leading to a slight increase of housing price returns of 5.8 basis points. Accounting for compounding shows that housing price returns actually *decrease* by 20 basis points. The policy implications of these two estimates are drastically different. In the case where compounding is not accounted for, hurricanes can be considered a form of fiscal stimulus, and little spending may be needed to aid in local recovery. However, we see that hurricanes adversely impact housing markets when compounding is accounted for, implying that fiscal support may be needed to help local areas recover from disasters.

We encourage researchers to conduct an analysis similar to that in Table 8 when analyzing natural disasters. The results in columns (1) and (2) show the economic effect of a natural disaster in the absence of compounding.

Columns (3) and (4) provide estimates for how compounding of natural disasters affects different economic outcomes. Note that if the estimates of $\beta_2$ and $\beta_3$ from Equation 4 are statistically insignificant, this implies that natural disaster compounding is unlikely to bias

the regression estimates in columns (1) and (2). Given in this example, the coefficients in these regressions were statistically significant, this provides reason to believe the estimates in a regression not accounting for the presence of natural disaster compounding may be biased. If columns (1) or (2) are statistically significant conducting the back-of-the-envelope calculation presented in this section could provide researchers a tool to estimate the bias presented by failing to account for the possibility of natural disaster compounding.

Finally, columns (5) and (6) provide regression results using Conley (1999) standard errors. Running regressions using these standard errors, or other standard errors that account for spatial correlation between units, could indicate whether disaster compounding presents issues for inference. As these results were very similar to those in columns (1) and (2), this suggests that in this setting it is reasonable to use standard errors double-clustered at the county and month levels.

# 6 Conclusion

The spatial footprint of natural disasters influences the intensity of damages that occur, and damages from natural disasters tend to be spatially correlated. In this paper, we provide a tool allowing researchers to account for correlations in damages from natural disasters across counties. We find that accounting for compounding increases the skewness of the distribution of disaster damages. We also find evidence consistent with compounding of natural disaster damages within spatial clusters. The method introduced in this paper provides researchers with a useful tool to further study how natural disaster compounding can affect economic outcomes following disasters.

The analysis of housing price returns highlights the most severe possible outcome of ignoring natural disaster compounding. Consider the results of the regression of house price returns on hurricane damages, without any natural disaster compounding. A natural policy implication of these regression results is that no county-level investment is needed after a hurricane to maintain house price returns, as housing price returns increase after a hurricane.

However, the results of the regression incorporating compounding show that in reality, housing price returns tend to decline following a hurricane once compound effects related to damages felt throughout the rest of the cluster are accounted for. Failing to account for compounding could lead policy makers to underinvest in local areas after hurricanes, insofar as policy makers are concerned with maintaining house price returns.

For this reason, the toolbox provided in this paper to construct natural disaster clusters, and analyze compounding effects associated with these clusters, is a valuable tool for researchers to better understand the economic effects of natural disasters. Examining whether standard errors are affected by spatial autocorrelation, and estimates are biased due to compounding, can allow for better empirical work on natural disasters, which can ultimately inform better policy decision-making.

# References


Acharya, V. V., Johnson, T., Sundaresan, S., and Tomunen, T. (2022). *Is Physical Climate Risk Priced? Evidence from Regional Variation in Exposure to Heat Stress*. Number w30445. National Bureau of Economic Research Cambridge, MA, USA.

Allen, L., Shan, Y., and Shen, Y. (2023). Do fintech mortgage lenders fill the credit gap? Evidence from natural disasters. *Journal of Financial and Quantitative Analysis*, 58(8):3342––3383.

Alok, S., Kumar, N., and Wermers, R. (2020). Do fund managers misestimate climatic disaster risk. *The Review of Financial Studies*, 33(3):1146–1183.

Aretz, K., Banerjee, S., and Pryshchepa, O. (2019). In the path of the storm: Does distress risk cause industrial firms to risk-shift? *Review of Finance*, 23(6):1115–1154.

Auh, J. K., Choi, J., Deryugina, T., and Park, T. (2022). Natural disasters and municipal bonds. Technical report, National Bureau of Economic Research.

Bakkensen, L. and Barrage, L. (2018). Climate shocks, cyclones, and economic growth: Bridging the micro-macro gap. Technical report, National Bureau of Economic Research.

Baldauf, M., Garlappi, L., and Yannelis, C. (2020). Does climate change affect real estate prices? Only if you believe in it. *The Review of Financial Studies*, 33(3):1256–1295.

Bena, J., Dinc, S., and Erel, I. (2022). The international propagation of economic downturns through multinational companies: The real economy channel. *Journal of Financial Economics*, 146(1):277–304.

Berg, G. and Schrader, J. (2012). Access to credit, natural disasters, and relationship lending. *Journal of Financial Intermediation*, 21(4):549–568.

Berg, T., Reisinger, M., and Streitz, D. (2021). Spillover effects in empirical corporate finance. *Journal of Financial Economics*, 142(3):1109–1127.

Bernile, G., Bhagwat, V., and Rau, P. R. (2017). What doesn't kill you will only make you more risk-loving: Early-life disasters and CEO behavior. *The Journal of Finance*, 72(1):167–206.

Bevacqua, E., Zappa, G., Lehner, F., and Zscheischler, J. (2022). Precipitation trends determine future occurrences of compound hot-dry events. *Nature Climate Change*, 12(4):350––355.

Bharath, S. T. and Cho, D. (2023). Do natural disaster experiences limit stock market participation? *Journal of Financial and Quantitative Analysis*, 58(1):29–70.

Billings, S. B., Gallagher, E. A., and Ricketts, L. (2022). Let the rich be flooded: The distribution of financial aid and distress after Hurricane Harvey. *Journal of Financial Economics*, 146(2):797–819.

Bleemer, Z. and van der Klaauw, W. (2019). Long-run net distributionary effects of federal disaster insurance: The case of Hurricane Katrina. *Journal of Urban Economics*, 110:70–88.

Blickle, K., Hamerling, S. N., and Morgan, D. P. (2021). How bad are weather disasters for banks? *FRB of New York Staff Report*, (990).

Blickle, K. and Santos, J. A. (2022). Unintended consequences of "mandatory" flood insurance. Technical report, Staff Report.

Botzen, W. W., Deschenes, O., and Sanders, M. (2019). The economic impacts of natural disasters: A review of models and empirical studies. *Review of Environmental Economics and Policy*.

Boustan, L. P., Kahn, M. E., Rhode, P. W., and Yanguas, M. L. (2020). The effect of natural disasters on economic activity in US counties: A century of data. *Journal of Urban Economics*, 118:103257.

Brown, J. R., Gustafson, M. T., and Ivanov, I. T. (2021). Weathering cash flow shocks. *The Journal of Finance*, 76(4):1731–1772.

Cameron, A. C. and Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of human resources*, 50(2):317–372.

Cavallo, E., Galiani, S., Noy, I., and Pantano, J. (2013). Catastrophic natural disasters and economic growth. *Review of Economics and Statistics*, 95(5):1549–1561.

Cheng, J., Qian, W., and Reeb, D. M. (2020). The ownership complaint gap: Mutual versus stock intermediaries. *Journal of Financial and Quantitative Analysis*, 55(5):1685–1715.

Choi, S., Park, R. J., and Xu, S. (2023). The strategic use of corporate philanthropy: Evidence from bank donations. *Review of Finance*, 27(5):1883–1930.

Chudik, A., Ellis, C. M., and Jaspersen, J. G. (2025). Lags, leave-outs and fixed effects. *Federal Reserve Bank of Dallas Working paper*, 2536.

Collier, B. L., Powell, L. S., Ragin, M. A., and You, X. (2024). Financing negative shocks: Evidence from Hurricane Harvey. *Journal of Financial and Quantitative Analysis*, pages 1–84.

Conley, T. G. (1999). Gmm estimation with cross sectional dependence. *Journal of econometrics*, 92(1):1–45.

Correa, R., He, A., Herpfer, C., and Lel, U. (2022). The rising tide lifts some interest rates: Climate change, natural disasters, and loan pricing. *International Finance Discussion Paper*, (1345).

Cortés, K. R. and Strahan, P. E. (2017). Tracing out capital flows: How financially integrated banks respond to natural disasters. *Journal of Financial Economics*, 125(1):182–199.

Crosignani, M. and Hiti, M. (2025). Estimating the cost: New insights from comprehensive open source data on damages from natural disasters in the U.S. Technical report, Working Paper.

del Valle, A., Scharlemann, T., and Shore, S. (2024). Household financial decision-making after natural disasters: Evidence from Hurricane Harvey. *Journal of Financial and Quantitative Analysis*, 59(5):2459—2485.

Deryugina, T. (2017). The fiscal cost of hurricanes: Disaster aid versus social insurance. *American Economic Journal: Economic Policy*, 9(3):168–198.

Deryugina, T., Kawano, L., and Levitt, S. (2018). The economic impact of Hurricane Katrina on its victims: Evidence from individual tax returns. *American Economic Journal: Applied Economics*, 10(2):202–233.

Dessaint, O. and Matray, A. (2017). Do managers overreact to salient risks? Evidence from hurricane strikes. *Journal of Financial Economics*, 126(1):97–121.

Diamond, W., Jiang, Z., and Ma, Y. (2024). The reserve supply channel of unconventional monetary policy. *Journal of Financial Economics*, 159:103887.

Dlugosz, J., Gam, Y. K., Gopalan, R., and Skrastins, J. (2023). Decision-making delegation in banks. *Management Science*, 70(5):3281–3301.

Do, V., McBrien, H., Flores, N. M., Northrop, A. J., Schlegelmilch, J., Kiang, M. V., and Casey, J. A. (2023). Spatiotemporal distribution of power outages with climate events and social vulnerability in the USA. *Nature Communications*, 14(1):2470.

Du, F. (2022). From playground to boardroom: Endowed social status and managerial performance. *Journal of Financial and Quantitative Analysis*, 57(3):988–1022.

Elkamhi, R., Jo, C., and Salerno, M. (2024). Measuring "state-level" economic policy uncertainty. *Journal of Financial and Quantitative Analysis*, 59(7):3230–3266.

Ersahin, N., Giannetti, M., and Huang, R. (2024). Trade credit and the stability of supply chains. *Journal of financial economics*, 155:103830.

Fich, E. M. and Xu, G. (2025). Do salient climatic risks affect shareholder voting? *Review of Finance*, 29(2):567–602.

Fu, S., Zhang, H., Zhong, Q., Chen, Q., Liu, A., Yang, J., and Pang, J. (2023). Spatiotemporal variations of precipitation concentration influenced by large-scale climatic factors and potential links to flood-drought events across China 1958–2019. *Atmospheric Research*, 282:106507.

Gallagher, E. A., Billings, S. B., and Ricketts, L. R. (2023). Human capital investment after the storm. *The Review of Financial Studies*, 36(7):2651–2684.

Gallagher, J. (2014). Learning about an infrequent event: Evidence from flood insurance take-up in the United States. *American Economic Journal: Applied Economics*, pages 206–233.

Gallagher, J. and Hartley, D. (2017). Household finance after a natural disaster: The case of Hurricane Katrina. *American Economic Journal: Economic Policy*, 9(3):199–228.

Gao, M., Liu, Y.-J., and Shi, Y. (2020). Do people feel less at risk? Evidence from disaster experience. *Journal of Financial Economics*, 138(3):866–888.

Ge, S. (2022). How do financial constraints affect product pricing? Evidence from weather and life insurance premiums. *The Journal of Finance*, 77(1):449–503.

Ge, S. and Weisbach, M. S. (2021). The role of financial conditions in portfolio choices: The case of insurers. *Journal of Financial Economics*, 142(2):803–830.

Hasan, I., Manfredonia, S., and Noth, F. (2024). Church membership and economic recovery: Evidence from the 2005 hurricane season. *The Economic Journal*, 134(664):3306–3332.

Heimer, R. Z., Myrseth, K. O. R., and Schoenle, R. S. (2019). YOLO: Mortality beliefs and household finance puzzles. *The Journal of Finance*, 74(6):2957–2996.

Huynh, T. D. and Xia, Y. (2023). Panic selling when disaster strikes: Evidence in the bond and stock markets. *Management Science*, 69(12):7448–7467.

Issler, P., Stanton, R., Vergara-Alert, C., and Wallace, N. (2021). Housing and mortgage markets with climate risk: Evidence from California wildfires.

Janizadeh, S., Pal, S. C., Saha, A., Chowdhuri, I., Ahmadi, K., Mirzaei, S., Mosavi, A. H., and Tiefenbacher, J. P. (2021). Mapping the spatial and temporal variability of flood hazard affected by climate and land-use changes in the future. *Journal of Environmental Management*, 298:113551.

Jerch, R., Kahn, M. E., and Lin, G. C. (2023). Local public finance dynamics and hurricane shocks. *Journal of Urban Economics*, 134:103516.

Jha, M., Liu, H., and Manela, A. (2021). Natural disaster effects on popular sentiment toward finance. *Journal of Financial and Quantitative Analysis*, 56(7):2584—2604.

Kim, H. S., Matthes, C., and Phan, T. (2022). Severe weather and the macroeconomy. *Federal Reserve Bank of Richmond Working Papers, 21-14R*.

Koetter, M., Noth, F., and Rehbein, O. (2020). Borrowers under water! Rare disasters, regional banks, and recovery lending. *Journal of Financial Intermediation*, 43:100811.

Kruttli, M. S., Roth Tran, B., and Watugala, S. W. (2023). Pricing poseidon: Extreme weather uncertainty and firm return dynamics. *Available at SSRN 3284517*.

Lange, S., Volkholz, J., Geiger, T., Zhao, F., Vega, I., Veldkamp, T., Reyer, C. P., Warszawski, L., Huber, V., Jägermeyr, J., et al. (2020). Projecting exposure to extreme climate impact events across six event categories and three spatial scales. *Earth's Future*, 8(12):e2020EF001616.

Leonard, M., Westra, S., Phatak, A., Lambert, M., van den Hurk, B., McInnes, K., Risbey, J., Schuster, S., Jakob, D., and Stafford-Smith, M. (2014). A compound event framework for understanding extreme impacts. *Wiley Interdisciplinary Reviews: Climate Change*, 5(1):113–128.

Li, C.-j., Chai, Y.-q., Yang, L.-s., and Li, H.-r. (2016). Spatio-temporal distribution of flood disasters and analysis of influencing factors in africa. *Natural Hazards*, 82:721–731.

Li, Q., Shan, H., Tang, Y., and Yao, V. (2024). Corporate climate risk: Measurements and responses. *The Review of Financial Studies*, 37(6):1778–1830.

Lian, J., Xu, K., and Ma, C. (2013). Joint impact of rainfall and tidal level on flood risk in a coastal city with a complex river network: A case study of Fuzhou City, China. *Hydrology and Earth System Sciences*, 17(2):679–689.

Liang, H. and Vansteenkiste, C. (2025). Disaster relief, inc.: When is corporate philanthropy good or bad for shareholders? *Review of Finance*, 29(3):851–886.

Lim, I. and Nguyen, D. D. (2021). Hometown lending. *Journal of Financial and Quantitative Analysis*, 56(8):2894–2933.

Lin, N., Emanuel, K., Oppenheimer, M., and Vanmarcke, E. (2012). Physically based assessment of hurricane surge threat under climate change. *Nature Climate Change*, 2(6):462–467.

Manconi, A., Massa, M., and Zhang, L. (2015). Bondholder concentration and credit risk: Evidence from a natural experiment. *Review of Finance*, 20(1):127–159.

Marfè, R. and Pénasse, J. (2024). Measuring macroeconomic tail risk. *Journal of Financial Economics*, 156:103838.

Marsooli, R., Lin, N., Emanuel, K., and Feng, K. (2019). Climate change exacerbates hurricane flood hazards along US Atlantic and Gulf coasts in spatially varying patterns. *Nature Communications*, 10(1):3785.

Masulis, R. W. and Reza, S. W. (2014). Agency problems of corporate philanthropy. *The Review of Financial Studies*, 28(2):592–636.

Merz, B., Blöschl, G., Vorogushyn, S., Dottori, F., Aerts, J. C., Bates, P., Bertola, M., Kemter, M., Kreibich, H., Lall, U., et al. (2021). Causes, impacts and patterns of disastrous river floods. *Nature Reviews Earth & Environment*, 2(9):592–609.

Morse, A. (2011). Payday lenders: Heroes or villains? *Journal of Financial Economics*, 102(1):28–44.

Perera, A., Nik, V. M., Chen, D., Scartezzini, J.-L., and Hong, T. (2020). Quantifying the impacts of climate change and extreme climate events on energy systems. *Nature Energy*, 5(2):150–159.

Ridder, N., Ukkola, A., Pitman, A., and Perkins-Kirkpatrick, S. (2022). Increased occurrence of high impact compound events under climate change. *Npj Climate and Atmospheric Science*, 5(1):3.

Roth Tran, B. and Wilson, D. J. (2025). The local economic impact of natural disasters. *Journal of the Association of Environmental and Resource Economists*, 12(6):1667–1704.

Sarhadi, A., Ausín, M. C., Wiper, M. P., Touma, D., and Diffenbaugh, N. S. (2018). Multidimensional risk in a nonstationary climate: Joint probability of increasingly severe warm and dry conditions. *Science Advances*, 4(11):eaau3487.

Sastry, P. (2021). Who bears flood risk? Evidence from mortgage markets in Florida. *Working Paper*.

Sastry, P., Sen, I., and Tenekedjieva, A.-M. (2023). When insurers exit: Climate losses, fragile insurers, and mortgage markets. *Fragile Insurers, and Mortgage Markets (December 23, 2023)*.

Schüwer, U., Lambert, C., and Noth, F. (2019). How do banks react to catastrophic events? evidence from Hurricane Katrina. *Review of Finance*, 23(1):75–116.

Skidmore, M. and Toya, H. (2002). Do natural disasters promote long-run growth? *Economic Inquiry*, 40(4):664–687.

Smirnov, N. V. (1939). Estimate of deviation between empirical distribution functions in two independent samples. *Bulletin Moscow University*, 2(2):3–16.

Stone Jr, B., Mallen, E., Rajput, M., Gronlund, C. J., Broadbent, A. M., Krayenhoff, E. S., Augenbroe, G., O'Neill, M. S., and Georgescu, M. (2021). Compound climate and infrastructure events: How electrical grid failure alters heat wave risk. *Environmental Science & Technology*, 55(10):6957–6964.

Thiery, W., Lange, S., Rogelj, J., Schleussner, C.-F., Gudmundsson, L., Seneviratne, S. I., Andrijevic, M., Frieler, K., Emanuel, K., Geiger, T., et al. (2021). Intergenerational inequities in exposure to climate extremes. *Science*, 374(6564):158–160.

Tigchelaar, M., Battisti, D. S., Naylor, R. L., and Ray, D. K. (2018). Future warming increases probability of globally synchronized maize production shocks. *Proceedings of the National Academy of Sciences*, 115(26):6644–6649.

Tomunen, T. (2025). Failure to share natural disaster risk. *The Review of Financial Studies*, page hhaf055.

Tran, B. R., Wilson, D. J., et al. (2020). The local economic impact of natural disasters. Federal Reserve Bank of San Francisco.

Wahl, T., Jain, S., Bender, J., Meyers, S. D., and Luther, M. E. (2015). Increasing risk of compound flooding from storm surge and rainfall for major US cities. *Nature Climate Change*, 5(12):1093–1097.

Wheater, H. S., Chandler, R. E., Onof, C., Isham, V. S., Bellone, E., Yang, C., Lekkas, D., Lourmas, G., and Segond, M.-L. (2005). Spatial-temporal rainfall modelling for flood risk estimation. *Stochastic Environmental Research and Risk Assessment*, 19:403–416.

Woodruff, J. D., Irish, J. L., and Camargo, S. J. (2013). Coastal flooding by tropical cyclones and sea-level rise. *Nature*, 504(7478):44–52.

Zhang, W., Villarini, G., Vecchi, G. A., and Smith, J. A. (2018). Urbanization exacerbated the rainfall and flooding caused by Hurricane Harvey in Houston. *Nature*, 563(7731):384–388.

Zhou, S., Yu, B., and Zhang, Y. (2023). Global concurrent climate extremes exacerbated by anthropogenic climate change. *Science Advances*, 9(10):eabo1638.

Zscheischler, J., Martius, O., Westra, S., Bevacqua, E., Raymond, C., Horton, R. M., van den Hurk, B., AghaKouchak, A., Jézéquel, A., Mahecha, M. D., et al. (2020). A typology of compound weather and climate events. *Nature Reviews Earth & Environment*, 1(7):333–347.

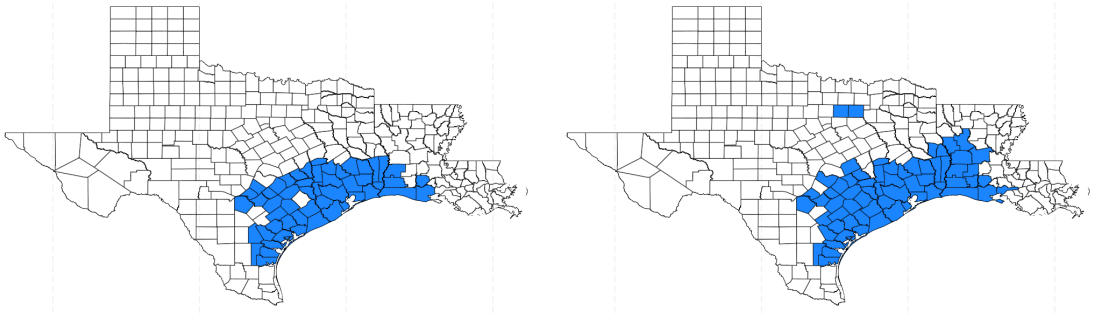
Zscheischler, J., Westra, S., Van Den Hurk, B. J., Seneviratne, S. I., Ward, P. J., Pitman, A., AghaKouchak, A., Bresch, D. N., Leonard, M., Wahl, T., et al. (2018). Future climate risk from compound events. *Nature Climate Change*, 8(6):469–477.

# Figures

Figure 1: Spatial Cluster Example: Hurricane Harvey

(a) Spatial Cluster

(b) Presidential Disaster Declaration

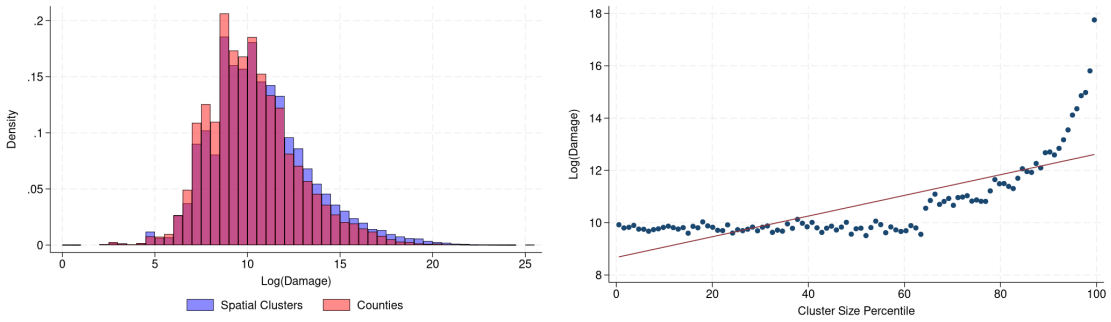


Notes: This figure illustrates the set of counties that are included in the Harris County August 2017 spatial cluster as obtained in the procedure outlined in subsubsection 2.2.1 (left), and the set of counties included in the "Hurricane Harvey" Presidential Disaster Declaration (right).

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.

Table 1: Summary of Papers Using Natural Disaster Data

| **Paper** | **Dependent Variable** | **Independent Variable** | **Dataset Source** |
|---|---|---|---|
| Tomunen (2025) | catastrophe bond pricing | occurence of disasters | Natural disaster data from 13 countries |
| Allen et al. (2023) | mortgage loan demand | disaster exposure as exogenous demand shock | FEMA |
| Alok et al. (2020) | portfolio managers' investment decisions | salience of/proximity to natural disasters | SHELDUS |
| Aretz et al. (2019) | risk-shifting decisions | natural disaster exposure | SHELDUS |
| Baldauf et al. (2020) | residential real estate price | sea-level inundation risk | NOAA |
| Bena et al. (2022) | multinational company investment and employment | natural disaster severity | EM-DAT |
| Bernile et al. (2017) | firm risk-taking decisions | CEO disaster exposure in childhood | SHELDUS, NOAA, USGS, *Science Daily*, tsunamis.findthedata.org, web searches |
| Bharath and Cho (2023) | households' portfolio risk taking | natural disaster exposure | FEMA, EM-DAT |
| Billings et al. (2022) | individual delinquency and bankruptcy status | natural disaster severity | FEMA, USGS |
| Brown et al. (2021) | credit line draws, size, and slack; loan contract terms | disaster severity as exogenous cash flow shock | NOAA |
| Cheng et al. (2020) | consumer insurance complaints | disaster exposure as exogenous insurance claims shock | SHELDUS |
| Choi et al. (2023) | bank charitable donations | natural disaster exposure | SHELDUS |
| Cortés and Strahan (2017) | bank credit supply | natural disaster exposure | SHELDUS |
| del Valle et al. (2024) | credit conditions on new and existing credit lines | natural disaster severity | FEMA |
| Dessaint and Matray (2017) | managers' cash holdings | natural disaster exposure | SHELDUS, FEMA, NOAA |
| Diamond et al. (2024) | deposits in banks and other markets | disaster damages as exogenous interest rate shock | SHELDUS |
| Dlugosz et al. (2023) | deposit rates/volumes, mortgage lending decisions, and house prices | natural disaster exposure and damages | SHELDUS, FEMA |
| Du (2022) | CEO managerial performance | disaster damages as exogenous familial wealth shock | SHELDUS |
| Elkamhi et al. (2024) | text-based measure of state-level policy uncertainty | natural disaster severity | SHELDUS |
| Ersahin et al. (2024) | trade credit allocation | natural disaster exposure | SHELDUS |

| Paper | Dependent Variable | Independent Variable | Dataset Source |
|---|---|---|---|
| Fich and Xu (2025) | mutual fund environmental proposal endorsement | natural disaster exposure | NOAA |
| Gallagher et al. (2023) | student debt and higher educational attainment | natural disaster severity | FEMA |
| Gao et al. (2020) | portfolio ratio of life insurance | earthquake severity | Seismological Society of Japan, Japan Meteorological Agency |
| Ge and Weisbach (2021) | life insurance premiums | unexpected disaster damages as exogenous P&C insurance losses shock | SHELDUS |
| Ge (2022) | P&C insurers' portfolio holdings | unexpected disaster damages as exogenous P&C insurance losses shock | SHELDUS |
| Heimer et al. (2019) | individual savings decisions | subjective estimates of natural disaster risk | SHELDUS |
| Huynh and Xia (2023) | bond and stock prices | natural disaster exposure and severity | SHELDUS |
| Jha et al. (2021) | text-based measure of finance sentiment | natural disaster severity | EM-DAT |
| Kruttli et al. (2023) | implied volatility, volatility risk premium | natural disaster exposure | NOAA |
| Li et al. (2024) | text-based measure of corporate climate risk | natural disaster exposure | SHELDUS |
| Liang and Vansteenkiste (2025) | cumulative abnormal returns | disaster date as exogenous disaster relief donations shock | EM-DAT |
| Lim and Nguyen (2021) | bank lending and credit allocation to CEO hometown | natural disaster severity | SHELDUS |
| Manconi et al. (2015) | credit risk | disaster exposure as exogenous bondholder concentration shock | Holborn Corporation 2005 report on Hurricane Katrina damages |
| Marfè and Pénasse (2024) | macroeconomic tail risk (consumption) | disaster as macroeconomic predictor variable | NOAA |
| Masulis and Reza (2014) | CEO compensation | disaster exposure as exogenous corporate giving shock | EM-DAT |
| Morse (2011) | household economic distress | natural disaster exposure | SHELDUS |
| Schüwer et al. (2019) | bank risk-based capital ratio | natural disaster exposure | FEMA |

Notes: This table lists all papers published in top finance journals using data involving the effects of natural disasters. The top finance journals are defined as *Journal of Finance*, *Journal of Financial and Quantitative Analysis*, *Journal of Financial Economics*, *Management Science*, *Review of*

*Finance* and *Review of Financial Studies*. The list was obtained for searching all papers in each of these journals for any mentions of either "SHELDUS" or "natural disaster", and then manually inspecting each article.

Table 2: 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 related to 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 3: Summary Statistics on Total Disaster Damages by Hazard – County-Level Data

| | All Damage (thousands of $) | | | | | | |
|---|---|---|---|---|---|---|---|
| | Count | Mean | SD | Median | 90th Pct. | 95th Pct. | 99th Pct. |
| 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 hazard-type, aggregated to the county-level. 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 4: Summary Statistics on Total Disaster Damages by Hazard – Spatial Cluster-Level Data

| | All Damage (thousands of $) | | | | | | |
|---|---|---|---|---|---|---|---|
| | Count | Mean | SD | Median | 90th Pct. | 95th Pct. | 99th Pct. |
| Hurricane | 251 | 1,515,411.8 | 9,206,264.8 | 402.4 | 717,977.0 | 5,183,330.6 | 28,754,559.3 |
| 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 hazard-type, aggregated to the spatial cluster-level. 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 5: Summary Statistics on Property and Crop Damage by Hazard – County-Level Data

| | Property Damage (thousands of $) | | | | | | |
|---|---|---|---|---|---|---|---|
| | Count | Mean | SD | Median | 90th Pct. | 95th Pct. | 99th Pct. |
| Hurricane | 2,907 | 112,289.2 | 1,077,798.3 | 250.0 | 38,958.3 | 152,580.2 | 2,013,503.0 |
| Earthquake | 112 | 60,860.6 | 275,912.3 | 10,256.4 | 20,398.4 | 76,109.1 | 1,019,616.2 |
| Coastal | 1,539 | 21,328.7 | 481,720.0 | 0.0 | 181.2 | 1,105.2 | 21,839.3 |
| Heat | 1,513 | 21,048.3 | 574,728.6 | 0.0 | 263.6 | 891.1 | 7,663.8 |
| Wildfire | 2,280 | 17,486.0 | 232,077.7 | 71.7 | 3,918.6 | 12,004.1 | 167,726.4 |
| Landslide | 976 | 16,027.6 | 213,651.8 | 22.3 | 3,222.1 | 17,673.4 | 142,381.2 |
| Tornado | 11,847 | 11,393.6 | 327,218.8 | 132.7 | 2,764.8 | 8,444.6 | 100,010.0 |
| Flooding | 30,597 | 11,279.9 | 327,081.6 | 61.1 | 1,822.5 | 5,689.9 | 64,808.0 |
| Lightning | 9,861 | 4,176.0 | 102,742.3 | 37.0 | 585.6 | 1,404.0 | 16,584.0 |
| Hail | 13,174 | 3,699.5 | 81,315.2 | 36.4 | 890.5 | 3,019.8 | 50,086.5 |
| Tsunami | 58 | 2,272.5 | 8,345.2 | 166.6 | 6,409.1 | 8,739.7 | 60,918.0 |
| Drought | 3,879 | 1,650.0 | 25,061.3 | 0.0 | 153.8 | 742.6 | 18,035.0 |
| Wind | 102,856 | 1,330.7 | 67,297.1 | 14.1 | 260.0 | 740.0 | 7,548.2 |
| Winter | 14,105 | 1,233.8 | 23,502.2 | 38.1 | 765.5 | 2,250.4 | 20,770.5 |
| Thunderstorm | 78,705 | 1,124.3 | 39,481.4 | 15.2 | 261.0 | 712.3 | 7,400.3 |
| Volcano | 19 | 888.1 | 3,672.9 | 55.5 | 148.0 | 16,054.7 | 16,054.7 |
| Fog | 317 | 355.6 | 2,057.4 | 49.4 | 527.8 | 1,118.3 | 4,792.8 |
| Avalanche | 1,055 | 353.9 | 7,399.2 | 0.0 | 15.3 | 101.1 | 2,529.1 |
| | Crop Damage (thousands of $) | | | | | | |
| Drought | 3,879 | 7,950.3 | 47,015.1 | 53.6 | 16,813.5 | 28,144.6 | 80,528.3 |
| Hurricane | 2,907 | 4,112.2 | 27,523.2 | 0.0 | 805.3 | 20,877.1 | 98,255.6 |
| Volcano | 19 | 1,552.8 | 5,958.6 | 0.0 | 1,221.8 | 26,096.4 | 26,096.4 |
| Wildfire | 2,280 | 1,056.7 | 28,018.1 | 0.0 | 6.4 | 64.6 | 10,930.4 |
| Hail | 13,174 | 600.0 | 5,852.0 | 0.0 | 284.9 | 1,165.3 | 15,670.2 |
| Heat | 1,513 | 591.2 | 7,613.5 | 0.0 | 0.0 | 58.3 | 4,661.2 |
| Winter | 14,105 | 552.1 | 10,092.5 | 0.0 | 0.0 | 114.2 | 7,585.1 |
| Flooding | 30,597 | 485.0 | 7,629.4 | 0.0 | 21.5 | 291.3 | 10,267.4 |
| Tornado | 11,847 | 414.0 | 8,837.4 | 0.0 | 12.0 | 159.6 | 3,653.6 |
| Lightning | 9,861 | 194.6 | 4,272.9 | 0.0 | 0.0 | 1.1 | 728.5 |
| Wind | 102,856 | 194.1 | 6,049.6 | 0.0 | 0.0 | 6.1 | 1,221.8 |
| Thunderstorm | 78,705 | 179.8 | 4,449.4 | 0.0 | 0.0 | 12.2 | 1,460.9 |
| Landslide | 976 | 173.3 | 2,023.8 | 0.0 | 0.0 | 11.1 | 8,668.0 |
| Coastal | 1,539 | 130.1 | 1,787.8 | 0.0 | 0.0 | 0.0 | 534.2 |
| Tsunami | 58 | 31.1 | 237.2 | 0.0 | 0.0 | 0.0 | 1,806.2 |
| Fog | 317 | 19.2 | 214.8 | 0.0 | 0.0 | 5.7 | 177.6 |
| Avalanche | 1,055 | 0.3 | 6.6 | 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 6: Summary Statistics on Property and Crop Damage by Hazard – Spatial Cluster-Level Data

| | Property Damage (thousands of $) | | | | | | |
|---|---|---|---|---|---|---|---|
| | Count | Mean | SD | Median | 90th Pct. | 95th Pct. | 99th Pct. |
| Hurricane | 251 | 1,462,571.6 | 9,084,690.0 | 394.5 | 522,450.1 | 4,801,737.6 | 28,750,380.8 |
| Earthquake | 28 | 243,551.9 | 855,175.1 | 1,387.6 | 775,056.4 | 800,000.0 | 4,468,203.6 |
| Heat | 756 | 202,426.9 | 3,493,693.1 | 0.0 | 11,140.8 | 47,055.8 | 2,585,458.1 |
| Drought | 316 | 180,844.7 | 1,394,458.6 | 78.1 | 51,741.9 | 250,909.5 | 7,374,072.0 |
| Landslide | 548 | 176,903.6 | 1,634,845.8 | 59.0 | 30,544.8 | 152,162.3 | 3,952,581.3 |
| Coastal | 967 | 170,655.9 | 3,212,088.4 | 0.0 | 3,988.4 | 21,839.3 | 725,038.6 |
| Tornado | 4,443 | 89,816.8 | 2,125,857.4 | 207.0 | 14,818.4 | 57,143.5 | 685,012.1 |
| Flooding | 7,836 | 60,000.2 | 1,650,261.5 | 78.8 | 7,516.9 | 30,128.2 | 444,015.0 |
| Wildfire | 1,061 | 57,019.4 | 634,813.8 | 210.2 | 18,868.0 | 62,445.5 | 1,101,922.2 |
| Hail | 4,359 | 52,252.7 | 1,544,189.1 | 67.2 | 11,298.9 | 49,137.7 | 523,857.4 |
| Lightning | 5,684 | 52,187.6 | 1,435,860.8 | 53.2 | 4,069.0 | 21,042.6 | 435,289.3 |
| Avalanche | 333 | 28,903.4 | 406,824.0 | 0.0 | 890.5 | 8,991.5 | 230,797.9 |
| Thunderstorm | 15,783 | 28,062.6 | 1,151,054.8 | 26.0 | 1,503.0 | 6,815.9 | 137,272.2 |
| Wind | 19,136 | 23,621.1 | 1,045,298.5 | 22.8 | 1,260.3 | 5,661.0 | 112,254.9 |
| Tsunami | 32 | 20,738.0 | 37,323.7 | 412.9 | 91,432.1 | 123,556.2 | 126,338.0 |
| Fog | 158 | 18,664.6 | 94,003.5 | 119.7 | 9,952.0 | 98,931.9 | 536,298.6 |
| Winter | 2,227 | 15,783.8 | 196,678.6 | 52.0 | 6,008.5 | 23,240.9 | 267,988.3 |
| Volcano | 11 | 1,534.0 | 4,817.8 | 11.4 | 444.0 | 16,054.7 | 16,054.7 |
| | Crop Damage (thousands of $) | | | | | | |
| Drought | 316 | 101,935.7 | 309,370.8 | 1,869.4 | 260,039.3 | 545,714.6 | 1,223,556.7 |
| Hurricane | 251 | 52,840.1 | 336,693.7 | 0.0 | 15,434.6 | 186,448.2 | 1,009,937.9 |
| Landslide | 548 | 14,774.9 | 166,374.8 | 0.0 | 33.6 | 786.8 | 257,959.0 |
| Heat | 756 | 14,773.4 | 143,724.6 | 0.0 | 14.8 | 2,062.6 | 347,932.6 |
| Fog | 158 | 9,607.2 | 101,568.8 | 0.0 | 71.2 | 14,278.9 | 79,876.5 |
| Wildfire | 1,061 | 8,545.9 | 109,268.7 | 0.0 | 54.8 | 1,300.2 | 134,452.9 |
| Coastal | 967 | 6,646.4 | 75,376.8 | 0.0 | 0.0 | 188.7 | 69,204.8 |
| Hail | 4,359 | 5,819.2 | 73,221.0 | 0.0 | 693.9 | 4,478.9 | 82,608.6 |
| Tornado | 4,443 | 5,368.3 | 64,822.3 | 0.0 | 114.2 | 1,954.9 | 79,876.5 |
| Flooding | 7,836 | 4,262.5 | 80,100.5 | 0.0 | 37.5 | 753.1 | 47,258.0 |
| Winter | 2,227 | 3,940.2 | 50,781.1 | 0.0 | 0.0 | 379.3 | 75,201.3 |
| Lightning | 5,684 | 3,211.2 | 49,983.3 | 0.0 | 4.2 | 337.6 | 41,063.0 |
| Volcano | 11 | 2,682.2 | 7,783.2 | 0.0 | 1,221.8 | 26,096.4 | 26,096.4 |
| Thunderstorm | 15,783 | 2,436.8 | 50,999.0 | 0.0 | 0.6 | 107.3 | 15,049.7 |
| Wind | 19,136 | 2,221.4 | 48,236.5 | 0.0 | 0.0 | 58.8 | 13,471.7 |
| Avalanche | 333 | 970.9 | 14,317.7 | 0.0 | 0.0 | 0.0 | 1,129.4 |
| Tsunami | 32 | 544.7 | 2,408.9 | 0.0 | 0.0 | 2,151.3 | 13,471.7 |
| 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 7: Relationship Between County- and Cluster-level Disaster Damage

| | $D_{i,t}$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Drought | | -5.807*** | | | | |
| | | (1.169) | | | | |
| Drought × Cluster Log Damage | | 0.432*** | | | | |
| | | (0.080) | | | | |
| Heat | | | 0.286 | | | |
| | | | (0.744) | | | |
| Heat × Cluster Log Damage | | | 0.022 | | | |
| | | | (0.050) | | | |
| Wildfire | | | | -1.058 | | |
| | | | | (0.657) | | |
| Wildfire × Cluster Log Damage | | | | 0.200*** | | |
| | | | | (0.048) | | |
| Flooding | | | | | -0.168 | |
| | | | | | (0.182) | |
| Flooding × Cluster Log Damage | | | | | 0.091*** | |
| | | | | | (0.013) | |
| Hurricane | | | | | | -1.743*** |
| | | | | | | (0.633) |
| Hurricane × Cluster Log Damage | | | | | | 0.182*** |
| | | | | | | (0.032) |
| Cluster Log Damage | 0.262*** | 0.248*** | 0.262*** | 0.261*** | 0.227*** | 0.243*** |
| | (0.011) | (0.011) | (0.011) | (0.011) | (0.012) | (0.010) |
| Log GDP | 0.699*** | 0.644*** | 0.696*** | 0.682*** | 0.664*** | 0.708*** |
| | (0.066) | (0.061) | (0.066) | (0.065) | (0.066) | (0.066) |
| 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) |
| Log Population | -0.583*** | -0.511*** | -0.583*** | -0.569*** | -0.549*** | -0.595*** |
| | (0.071) | (0.065) | (0.071) | (0.070) | (0.071) | (0.071) |
| Constant | 2.804*** | 2.976*** | 2.839*** | 2.882*** | 3.229*** | 3.060*** |
| | (0.302) | (0.296) | (0.301) | (0.293) | (0.297) | (0.288) |
| Observations | 115,739 | 115,739 | 115,739 | 115,739 | 115,739 | 115,739 |
| $R^2$ | 0.169 | 0.187 | 0.169 | 0.176 | 0.216 | 0.183 |

Notes: This table shows the results of a regression of log of total 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 8: Housing Price Returns and Hurricane Damages

This table displays results of a regression of year-over-year changes in house prices on hurricane damages at the county level, as well as rest-of-cluster hurricane damages. Regressions control for the natural log of county-GDP, county-level wages and the natural log of population. *, ** and *** indicate 10%, 5% and 1% significance, respectively. Standard errors, which are either double-clustered at the county and month levels or calculated per Conley (1999), are shown in parentheses.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Hurricane Damage (BN)$_{-11,0}$ | 0.011*** | 0.005* | 0.016*** | 0.011*** | 0.011*** | 0.005** |
| | (2.70) | (1.87) | (3.39) | (3.07) | (3.26) | (2.12) |
| Cluster Hurricane Damage (BN) | | | 0.011*** | -0.002* | | |
| | | | (7.55) | (-1.91) | | |
| Hurricane Damage (BN)$_{-11,0}\times$ Cluster Hurricane Damage (BN) | | | -0.005*** | -0.003** | | |
| | | | (-3.40) | (-2.20) | | |
| County Controls | Y | Y | | Y | Y | Y |
| County FE | | Y | | Y | | Y |
| Date FE | | Y | | Y | | Y |
| Conley SE | | | | | Y | Y |
| Mean | 0.034 | 0.034 | 0.034 | 0.034 | 0.034 | 0.034 |
| Adjusted-R2 | 0.004 | 0.469 | 0.003 | 0.469 | 0.004 | 0.003 |
| Observations | 418,317 | 418,317 | 463,934 | 418,317 | 418,317 | 418,317 |

# 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 over 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 affect 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, Gal-

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

lagher 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 pay down 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 enrollment appears to drop in the Texas counties that were 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) show 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) show that local German banks lend to firms affected by flooding and Berg and Schrader

(2012) show 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 that 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 that 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) combine 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 to the entry of riskier insurers, 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 find 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) show 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) find 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) find 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) find 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 show 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) find 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) provide 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 effects disappear, however, when controlling for major negative political events in the wake of these disasters. Bakkensen and Barrage (2018) also show 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 an assumption that 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) model 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 conven-

tional 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) argue 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) find that upstream rainfall can strain water drainage systems, leading to unanticipated flooding from high tides. Zhang et al. (2018)

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

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 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) model 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) model 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 geograph-

ically, 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 Calculation of Rescaled Damages

One issue in examining how county-level damage relates to cluster-level damage is that disasters affecting more counties may mechanically have more damage. To address this concern, we calculate another version of the cluster-level damage in order to adjust for mechanical increases in cluster-level damage due to the increasing size of the cluster. Specifically, we calculated the median damage for any county experiencing a certain hazard type, conditional on nonzero damage. For each county, we sum up the median hazard damage for all hazards experienced by that county, and scale the total damage by this sum of median hazard damages:

$$\bar{D}_{i,t} = \frac{\sum_{h \in H(c_t^i)} D_{i,t,h}}{\sum_{h \in H(c_t^i)} D_h^{median}}, \tag{5}$$

where $H(c_t^i)$ is the set of all hazards experienced by county $i$ in time $t$, $D_{i,t,h}$ is damages for hazard $h$ experienced in county $i$ at time $t$, and $D_h^{median}$ is the median damages observed for hazard $h$. We refer to $\bar{D}_{i,t}$ as the rescaled damage for county $i$ at time $t$. A similar measure can be calculated at the cluster-level using the cluster-level damages. Accordingly,

for each county, we calculate the rescaled cluster-level damage, for the cluster it is part of, while excluding the damage for the county of interest:

$$\begin{aligned} \bar{D}_{j,t}^{-i} &= \frac{\sum_{h \in H_{j,t}^{-i}} D_{j,t,h}}{\sum_{h \in H_j^{-i}} D_h^{median}}, \\ &= \frac{\sum_{h \in H_{j,t}} D_{j,t,h} - \sum_{h \in H_{i,t}} D_{i,t,h}}{\sum_{h \in H_j} D_h^{median} - \sum_{h \in H_i} D_h^{median}}, \end{aligned} \tag{6}$$

where $H_{j,t}$ is the set of all hazards experienced by cluster $j$ at time $t$, and $H_j$ is the set of all hazards experienced by cluster $j$ throughout the entire sample period.

Table IA.C.1: Compounding of Natural Disaster Damages with Rescaling

| | | | | | | $_{i,t}$ |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Drought=1 | | -0.028 | | | | |
| | | (0.155) | | | | |
| Drought=1 × $\bar{D}^{-i}_{j,t}$ | | 0.403*** | | | | |
| | | (0.078) | | | | |
| Heat=1 | | | -0.464*** | | | |
| | | | (0.128) | | | |
| Heat=1 × $\bar{D}^{-i}_{j,t}$ | | | 0.178** | | | |
| | | | (0.082) | | | |
| Wildfire=1 | | | | 0.254*** | | |
| | | | | (0.088) | | |
| Wildfire=1 × $\bar{D}^{-i}_{j,t}$ | | | | 0.217*** | | |
| | | | | (0.040) | | |
| Flooding=1 | | | | | 0.249*** | |
| | | | | | (0.033) | |
| Flooding=1 × $\bar{D}^{-i}_{j,t}$ | | | | | 0.122*** | |
| | | | | | (0.022) | |
| Hurricane=1 | | | | | | -0.452*** |
| | | | | | | (0.140) |
| Hurricane=1 × $\bar{D}^{-i}_{j,t}$ | | | | | | 0.125*** |
| | | | | | | (0.036) |
| $\bar{D}^{-i}_{j,t}$ | 0.472*** | 0.450*** | 0.472*** | 0.468*** | 0.436*** | 0.468*** |
| | (0.016) | (0.016) | (0.016) | (0.016) | (0.019) | (0.017) |
| Log GDP | 0.443*** | 0.416*** | 0.443*** | 0.439*** | 0.437*** | 0.443*** |
| | (0.048) | (0.044) | (0.048) | (0.047) | (0.048) | (0.048) |
| 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) |
| Log Population | -0.321*** | -0.285*** | -0.321*** | -0.319*** | -0.317*** | -0.321*** |
| | (0.052) | (0.048) | (0.052) | (0.052) | (0.052) | (0.052) |
| Constant | -3.699*** | -3.701*** | -3.710*** | -3.672*** | -3.717*** | -3.700*** |
| | (0.175) | (0.171) | (0.175) | (0.172) | (0.175) | (0.175) |
| Observations | 115,739 | 115,739 | 115,739 | 115,739 | 115,739 | 115,739 |
| $R^2$ | 0.230 | 0.239 | 0.230 | 0.232 | 0.238 | 0.231 |

Notes: This table shows the results of a regression of log of total 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. Rescaled damages, as described in Equation 5, are used in this analysis. 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.C.2: Housing Price Returns and Rescaled Hurricane Damages

This table displays results of a regression of changes in house prices on hurricane damages at the county level, as well as rest-of-cluster hurricane damages. Regressions control for the natural log of county-GDP, county-level wages and the natural log of population. Rescaled damages, as described in Equation 5, are used in this analysis. *, ** and *** indicate 10%, 5% and 1% significance, respectively. Standard errors, which are either double-clustered at the county and month levels or calculated per Conley (1999), are shown in parentheses.

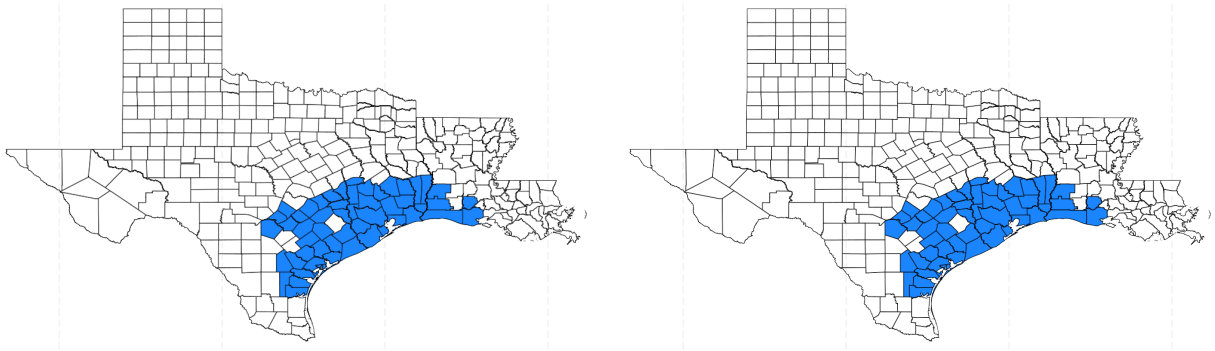
| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Rescaled Hurricane Damage$_{-11,0}$ | 0.039*** | 0.032*** | 0.203*** | 0.190*** | 0.039*** | 0.032*** |
| | (16.02) | (21.64) | (156.24) | (5.19) | (27.09) | (4.07) |
| Rescaled Cluster Hurricane Damage | | | -1819.983*** | -672.743 | | |
| | | | (-4.38) | (-1.52) | | |
| Rescaled Hurricane Damage$_{-11,0}\times$ Rescaled Cluster Hurricane Damage | | | -2457451.349*** | -2358094.648*** | | |
| | | | (-10740.75) | (-4.42) | | |
| County Controls | Y | Y | | Y | Y | Y |
| County FE | | Y | | Y | | Y |
| Date FE | | Y | | Y | | Y |
| Conley SE | | | | | Y | Y |
| Mean | 0.034 | 0.034 | 0.034 | 0.034 | 0.034 | 0.034 |
| Adjusted-R2 | 0.003 | 0.469 | 0.002 | 0.469 | 0.003 | 0.003 |
| Observations | 418,317 | 418,317 | 463,934 | 418,317 | 418,317 | 418,317 |

# IA.D Replication of Results Using Crosignani and Hiti (2025) LND Data

Figure IA.D.1: Harvey Spatial Cluster for SHELDUS and Crosignani and Hiti (2025) Data

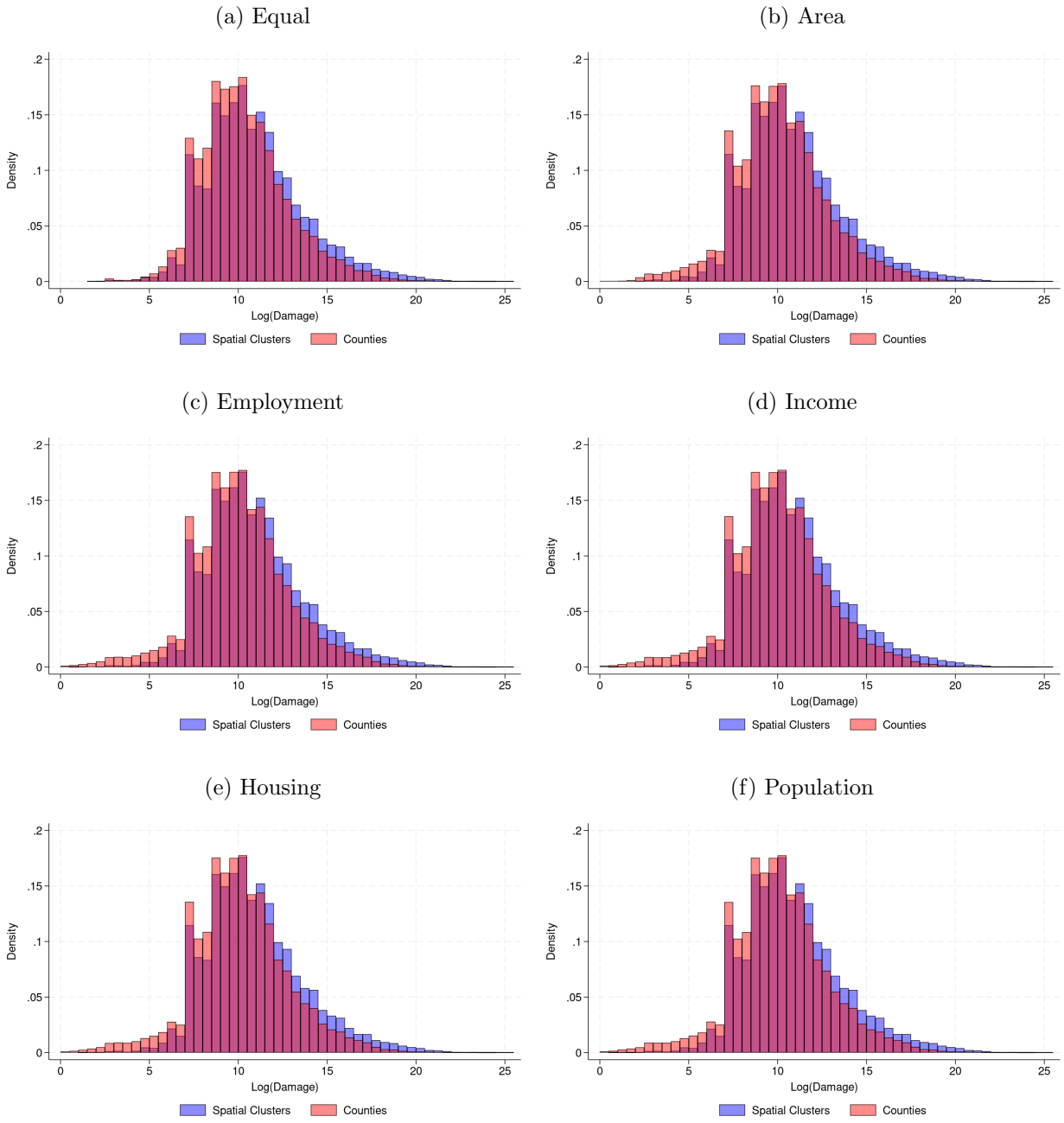
(a) SHELDUS

(b) Crosignani and Hiti (2025) LND Data



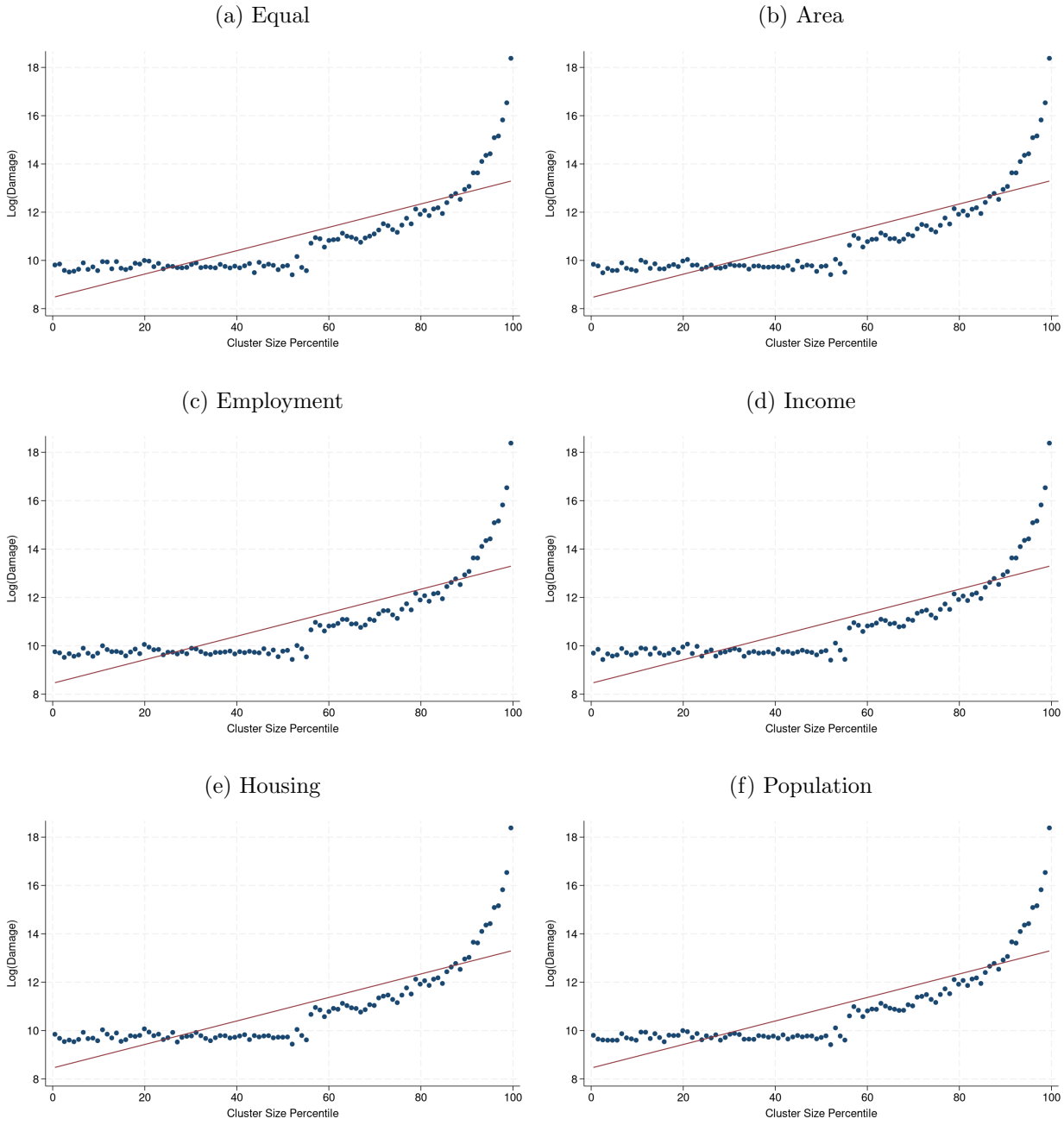
Notes: This figure illustrates the set of counties that are included in the Harris County August 2017 spatial cluster as obtained in the procedure outlined in subsubsection 2.2.1 using SHELDUS data (left), and the set of counties identified using the Crosignani and Hiti (2025) dataset (right).

Figure IA.D.2: Distribution of Damage Across Cluster with Crosignani and Hiti (2025) LND Data




Notes: This figure displays information on the distribution of damages across clusters. Each panel displays 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, for alternative weightings of the natural disasters data. The LND data from Crosignani and Hiti (2025) are used in generating the clusters.

Figure IA.D.3: Binscatter Plots Using Crosignani and Hiti (2025) LND Data




Notes: These plots show the expected log damage conditional on the size of the cluster it lies in, for different weightings of disaster data using this LND dataset from Crosignani and Hiti (2025).

Table IA.D.1: Compounding of Natural Disasters Damages Using the Crosignani and Hiti (2025) LND Weighting Scheme

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Cluster Log Damage | 0.234*** | 0.238*** | 0.235*** | 0.237*** | 0.238*** | 0.238*** |
| | (0.008) | (0.008) | (0.009) | (0.008) | (0.008) | (0.008) |
| Log GDP | 0.619*** | 0.624*** | 0.640*** | 0.622*** | 0.624*** | 0.621*** |
| | (0.065) | (0.065) | (0.060) | (0.065) | (0.065) | (0.065) |
| 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) |
| Log Population | -0.489*** | -0.455*** | -0.530*** | -0.458*** | -0.455*** | -0.452*** |
| | (0.070) | (0.074) | (0.064) | (0.073) | (0.074) | (0.074) |
| Constant | 3.039*** | 2.536*** | 3.365*** | 2.598*** | 2.523*** | 2.550*** |
| | (0.292) | (0.284) | (0.277) | (0.281) | (0.284) | (0.283) |
| Observations | 128,049 | 128,049 | 128,049 | 128,049 | 128,049 | 128,049 |
| $R^2$ | 0.121 | 0.119 | 0.138 | 0.119 | 0.119 | 0.119 |
| Weight | Area | Employment | Equal | Housing | Income | Population |

Notes: This table shows the results of a regression of log of total damages for county-level aggregates on 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. Alternative schemes of weighting the data from the LND dataset from Crosignani and Hiti (2025) are used. Standard errors are double-clustered at the county- and month-level. *, **, and *** indicate 10%, 5%, and 1% significance, respectively.

# IA.E Additional Tables and Figures

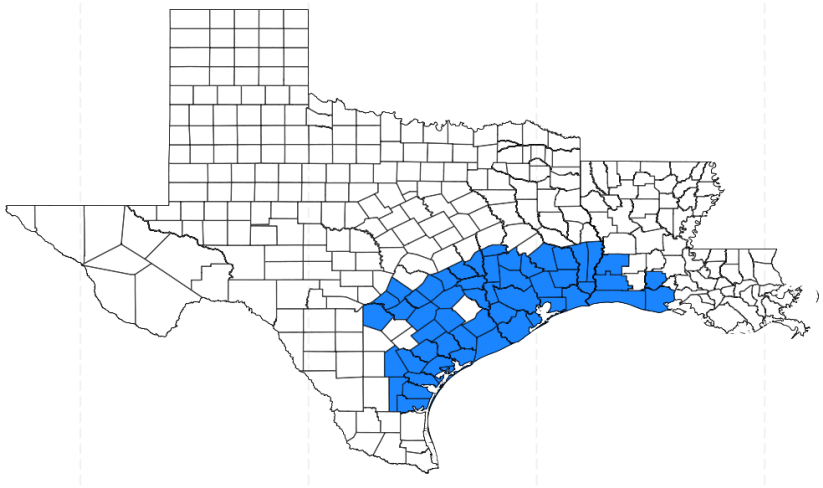
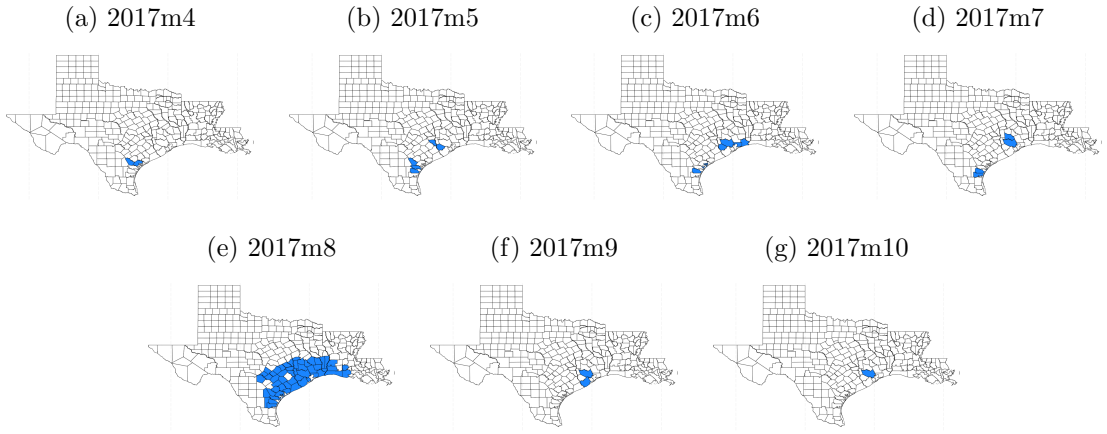


Figure IA.E.4: Spatiotemporal Cluster Containing Harris County, April-October 2017

Notes: 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.

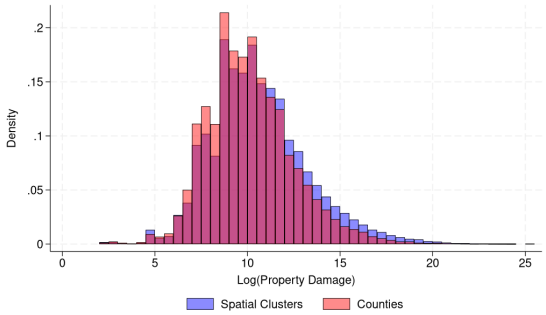
Figure IA.E.5: Temporal Evolution of Harris County Spatiotemporal Cluster, 04-10/2017



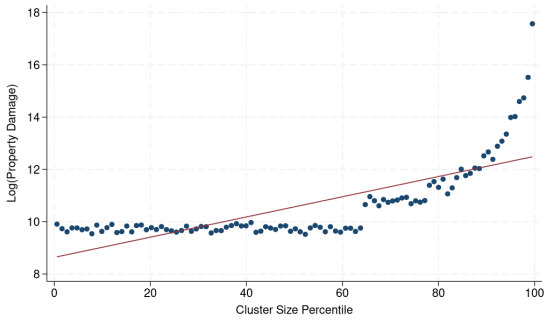

Notes: This figure illustrates the month-by-month evolution of the Harris County April-October 2017 spatiotemporal cluster, obtained following the process outlined in subsubsection 1.2.2.

Figure IA.E.6: Distribution of Property Damage Across Spatial Clusters

(a) Property Damage Histogram



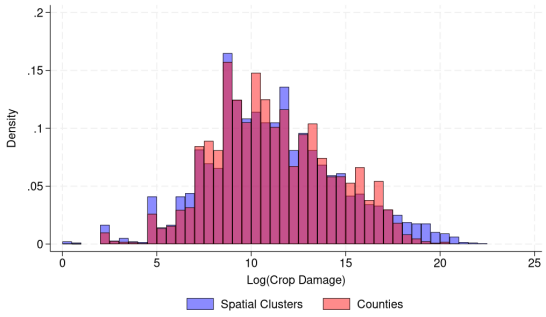

(b) Size vs Log(Property Damage)



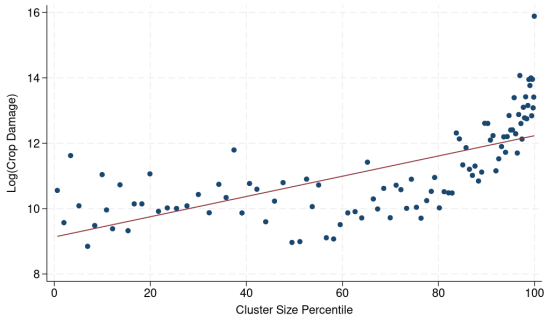

Notes: Panel (a) compares the distributions of the log of property damages, based on whether they are aggregated to the county level or to the spatial cluster level, following the process outlined in subsubsection 1.2.1. Panel (b) shows the expected log property damages conditional on the size of the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

Figure IA.E.7: Distribution of Crop Damage Across Spatial Clusters

(a) Crop Damage Histogram



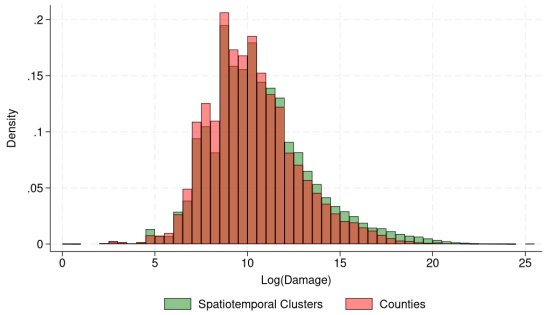

(b) Size vs Log(Crop Damage)



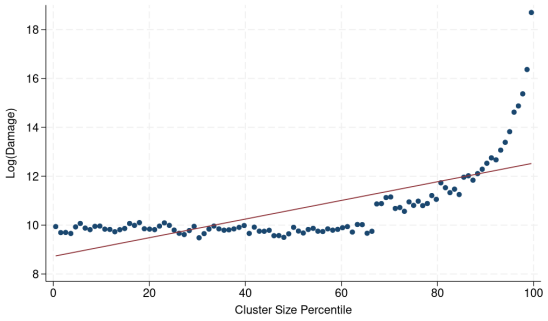

Notes: Panel (a) compares the distributions of the log of crop damages, based on whether they are aggregated to the county level or to the spatial cluster level, following the process outlined in subsubsection 1.2.2. Panel (b) shows the expected log crop damages conditional on the size of the spatiotemporal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

Figure IA.E.8: 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 1.2.1. 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.

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

| | All Damage (thousands of $) | | | | | | |
|---|---|---|---|---|---|---|---|
| | Count | Mean | SD | Median | 90th Pct. | 95th Pct. | 99th Pct. |
| Hurricane | 205 | 1,963,249.8 | 10,233,478.9 | 770.2 | 2,479,581.6 | 9,103,685.5 | 28,836,436.1 |
| Drought | 287 | 898,143.5 | 6,440,464.2 | 34,090.7 | 1,006,839.9 | 2,137,319.8 | 22,814,845.2 |
| 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.E.3: Spatial Cluster-Level Spillover Effects from Natural Disasters Using Property Damage

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Drought=1 | | 0.318 | | | | |
| | | (1.335) | | | | |
| Drought=1 × Cluster Log Damage | | 0.008 | | | | |
| | | (0.096) | | | | |
| Heat=1 | | | -0.082 | | | |
| | | | (0.680) | | | |
| Heat=1 × Cluster Log Damage | | | 0.033 | | | |
| | | | (0.045) | | | |
| Wildfire=1 | | | | -0.987 | | |
| | | | | (0.609) | | |
| Wildfire=1 × Cluster Log Damage | | | | 0.199*** | | |
| | | | | (0.045) | | |
| Flooding=1 | | | | | -0.367** | |
| | | | | | (0.171) | |
| Flooding=1 × Cluster Log Damage | | | | | 0.105*** | |
| | | | | | (0.012) | |
| Hurricane=1 | | | | | | -1.746*** |
| | | | | | | (0.655) |
| Hurricane=1 × Cluster Log Damage | | | | | | 0.185*** |
| | | | | | | (0.033) |
| Cluster Log Damage | 0.241*** | 0.241*** | 0.241*** | 0.240*** | 0.201*** | 0.220*** |
| | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.009) |
| Log GDP | 0.564*** | 0.561*** | 0.563*** | 0.548*** | 0.517*** | 0.569*** |
| | (0.059) | (0.058) | (0.058) | (0.057) | (0.057) | (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) |
| Log Population | -0.387*** | -0.383*** | -0.387*** | -0.374*** | -0.339*** | -0.394*** |
| | (0.059) | (0.059) | (0.059) | (0.058) | (0.058) | (0.059) |
| Constant | 2.846*** | 2.854*** | 2.871*** | 2.926*** | 3.342*** | 3.122*** |
| | (0.293) | (0.293) | (0.292) | (0.284) | (0.280) | (0.274) |
| Observations | 111,856 | 111,856 | 111,856 | 111,856 | 111,856 | 111,856 |
| $R^2$ | 0.157 | 0.158 | 0.158 | 0.166 | 0.212 | 0.174 |

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 the damage indicator with the log of property 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.E.4: Spatial Cluster-Level Spillover Effects from Natural Disasters Using Crop Damage

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Drought=1 | | -4.764*** | | | | |
| | | (0.582) | | | | |
| Drought=1 × Cluster Log Damage | | 0.332*** | | | | |
| | | (0.044) | | | | |
| Heat=1 | | | -5.174* | | | |
| | | | (2.751) | | | |
| Heat=1 × Cluster Log Damage | | | 0.323* | | | |
| | | | (0.180) | | | |
| Wildfire=1 | | | | 0.040 | | |
| | | | | (1.392) | | |
| Wildfire=1 × Cluster Log Damage | | | | 0.030 | | |
| | | | | (0.104) | | |
| Flooding=1 | | | | | 1.631*** | |
| | | | | | (0.456) | |
| Flooding=1 × Cluster Log Damage | | | | | -0.117*** | |
| | | | | | (0.033) | |
| Hurricane=1 | | | | | | -0.825 |
| | | | | | | (1.436) |
| Hurricane=1 × Cluster Log Damage | | | | | | 0.117 |
| | | | | | | (0.086) |
| Cluster Log Damage | 0.602*** | 0.523*** | 0.601*** | 0.602*** | 0.642*** | 0.585*** |
| | (0.029) | (0.031) | (0.029) | (0.029) | (0.029) | (0.030) |
| Log GDP | 0.527*** | 0.508*** | 0.528*** | 0.521*** | 0.509*** | 0.571*** |
| | (0.107) | (0.094) | (0.107) | (0.107) | (0.103) | (0.108) |
| 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) |
| Log Population | -0.633*** | -0.575*** | -0.632*** | -0.628*** | -0.606*** | -0.693*** |
| | (0.116) | (0.101) | (0.116) | (0.116) | (0.112) | (0.118) |
| Constant | 1.529** | 2.363*** | 1.542** | 1.558** | 0.949 | 1.748** |
| | (0.681) | (0.648) | (0.678) | (0.680) | (0.668) | (0.687) |
| Observations | 12,367 | 12,367 | 12,367 | 12,367 | 12,367 | 12,367 |
| $R^2$ | 0.518 | 0.546 | 0.518 | 0.518 | 0.522 | 0.524 |

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 damage indicator with the log of property 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.E.5: Spatial Cluster-Level Spillover Effects from Natural Disasters with County and Time Fixed Effects

| | $D_{i,t}$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Drought=1 | | -3.875*** | | | | |
| | | (0.990) | | | | |
| Drought=1 × Cluster Log Damage | | 0.318*** | | | | |
| | | (0.065) | | | | |
| Heat=1 | | | -0.112 | | | |
| | | | (0.654) | | | |
| Heat=1 × Cluster Log Damage | | | 0.035 | | | |
| | | | (0.043) | | | |
| Wildfire=1 | | | | -0.624 | | |
| | | | | (0.608) | | |
| Wildfire=1 × Cluster Log Damage | | | | 0.157*** | | |
| | | | | (0.044) | | |
| Flooding=1 | | | | | -0.150 | |
| | | | | | (0.184) | |
| Flooding=1 × Cluster Log Damage | | | | | 0.087*** | |
| | | | | | (0.013) | |
| Hurricane=1 | | | | | | -1.603*** |
| | | | | | | (0.555) |
| Hurricane=1 × Cluster Log Damage | | | | | | 0.161*** |
| | | | | | | (0.035) |
| Cluster Log Damage | 0.274*** | 0.262*** | 0.274*** | 0.272*** | 0.240*** | 0.257*** |
| | (0.009) | (0.008) | (0.009) | (0.009) | (0.010) | (0.009) |
| Log GDP | 0.071 | 0.070 | 0.069 | 0.081 | 0.072 | 0.056 |
| | (0.090) | (0.086) | (0.090) | (0.090) | (0.091) | (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) |
| Log Population | -0.089 | -0.128 | -0.088 | -0.152 | -0.102 | -0.099 |
| | (0.257) | (0.244) | (0.257) | (0.256) | (0.265) | (0.250) |
| Constant | 6.171** | 6.771*** | 6.178** | 6.729*** | 6.553** | 6.697*** |
| | (2.525) | (2.474) | (2.525) | (2.500) | (2.537) | (2.460) |
| Observations | 115,712 | 115,712 | 115,712 | 115,712 | 115,712 | 115,712 |
| $R^2$ | 0.325 | 0.336 | 0.325 | 0.330 | 0.361 | 0.332 |
| County FE | Y | Y | Y | Y | Y | Y |
| Date FE | Y | Y | Y | Y | Y | Y |

Notes: This table shows the results of a regression of log of total 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 total 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.E.6: Spatial Cluster-Level Spillover Effects from Natural Disasters with County and State-by-Time Fixed Effects

| | $D_{i,t}$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Drought=1 | | -3.096** | | | | |
| | | (1.242) | | | | |
| Drought=1 × Cluster Log Damage | | 0.281*** | | | | |
| | | (0.080) | | | | |
| Heat=1 | | | -0.581 | | | |
| | | | (0.592) | | | |
| Heat=1 × Cluster Log Damage | | | 0.053 | | | |
| | | | (0.037) | | | |
| Wildfire=1 | | | | 0.897 | | |
| | | | | (0.573) | | |
| Wildfire=1 × Cluster Log Damage | | | | 0.051 | | |
| | | | | (0.040) | | |
| Flooding=1 | | | | | 0.006 | |
| | | | | | (0.149) | |
| Flooding=1 × Cluster Log Damage | | | | | 0.083*** | |
| | | | | | (0.010) | |
| Hurricane=1 | | | | | | -0.631 |
| | | | | | | (0.880) |
| Hurricane=1 × Cluster Log Damage | | | | | | 0.138*** |
| | | | | | | (0.050) |
| Cluster Log Damage | 0.176*** | 0.165*** | 0.176*** | 0.175*** | 0.149*** | 0.164*** |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.009) | (0.008) |
| Log GDP | 0.008 | 0.004 | 0.007 | 0.009 | 0.016 | 0.005 |
| | (0.070) | (0.066) | (0.070) | (0.071) | (0.070) | (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) |
| Log Population | -0.021 | -0.003 | -0.020 | -0.022 | -0.061 | -0.062 |
| | (0.175) | (0.173) | (0.175) | (0.174) | (0.169) | (0.169) |
| Constant | 7.841*** | 7.848*** | 7.837*** | 7.826*** | 8.303*** | 8.452*** |
| | (1.896) | (1.891) | (1.897) | (1.885) | (1.817) | (1.873) |
| Observations | 115,195 | 115,195 | 115,195 | 115,195 | 115,195 | 115,195 |
| $R^2$ | 0.509 | 0.513 | 0.509 | 0.511 | 0.536 | 0.513 |
| County FE | Y | Y | Y | Y | Y | Y |
| State-Date FE | Y | Y | Y | Y | Y | Y |

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 damage indicator with the log of total 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.E.7: Housing Market Changes and Hurricane Damages (Log1Plus Damages)

This table displays results of a regression of changes in house prices (panel (a) and mortgage originations (panel b) on hurricane damages at the county level, as well as rest-of-cluster hurricane damages. Log 1 plus damages are used to account for the skewness of the distribution. Regressions control for the natural log of county-GDP, county-level wages and the natural log of population. *, ** and *** indicate 10%, 5% and 1% significance, respectively. Standard errors, which are either double-clustered at the county and month levels or calculated per Conley (1999), are shown in parentheses.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Log 1 Plus Hurricane Damage$_{-11,0}$ | 0.048*** | 0.026*** | 0.063*** | 0.049*** | 0.048*** | 0.026*** |
| | (3.39) | (2.62) | (2.90) | (3.00) | (4.06) | (2.88) |
| Log 1 Plus Cluster Hurricane Damage | | | 0.027*** | -0.001 | | |
| | | | (7.65) | (-0.40) | | |
| Log 1 Plus Hurricane Damage$_{-11,0}$× Log 1 Plus Cluster Hurricane Damage | | | -0.038*** | -0.025** | | |
| | | | (-2.64) | (-2.03) | | |
| County Controls | Y | Y | | Y | Y | Y |
| County FE | | Y | | Y | | Y |
| Date FE | | Y | | Y | | Y |
| Conley SE | | | | | Y | Y |
| Mean | 0.034 | 0.034 | 0.034 | 0.034 | 0.034 | 0.034 |
| Adjusted-R2 | 0.004 | 0.469 | 0.005 | 0.469 | 0.004 | 0.003 |
| Observations | 418,317 | 418,317 | 463,934 | 418,317 | 418,317 | 418,317 |