Natural Disaster's Macroeconomic Impact on US States

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This dissertation is my own work and it includes nothing which is the outcome of work done in collaboration except what is specified in the text. It is not substantially the same as any work that has already been submitted before for any degree or other qualification except as specified in the text. It does not exceed the agreed word limit.

Abstract

This paper investigates the macroeconomic the frequency of natural disasters has on the state-level for the United States from 2011-2019. EM-DAT data and publicly available state-level measures are used as the variables of interest. A fixed effect regression model and GMM model is utilized to investigate the relationship between natural disasters and real GDP growth measures. While the fixed effects regression model finds a significant positive relationship, this result is contradicted by the insignificant results of the GMM model. Overall, the results of this study is inconclusive, with no true conclusion about the exact effect that natural disasters play.

Introduction

Natural disasters, as it names suggests, is an uncontrollable phenomenon that causes great damage both economically and in terms of human loss. With the impending effects of climate change coming into play, these natural disasters are happening increasingly common, being incorporated within daily life. However, despite these natural disaster occurrences becoming more common, they are not necessarily all within the same magnitude as the catastrophic ones that are heavily covered in both media and in literature.

Most of the exiting literature investigating the economic impact of natural disaster approaches the issue through two lenses: disaster-level effects or cross-country comparisons. With the studies of disaster-level effects, short-term results are obtained, with results pointing to the importance of the intensity of the event. For cross-country comparisons, long-term results spanning decades are investigating, finding country-specific characteristics and disaster type to be essential in determining the final effect of natural disasters. For within-country studies, most focusing on the United States look at county-level effects, based on the intensity of natural disasters measured by damages.

There are four main contributions this paper aims to make. First, this paper looks to add on to the current literature by testing a new measure for natural disasters, which is the duration that it lasts. This new measure, in addition to the lesser used measure of frequency of disasters, adds on to the sparser end of natural disaster economics research that looks specifically how the economy may be different due to the constant effects of natural disasters. Second, panel data at the state level is used within the investigation. While state level investigations have been done in other countries, such as China, it is an underinvestigated level for the United States. Third, this paper aims to add to the current debate regarding the positive or negative impacts of natural disasters by providing medium to long-run results through the investigation of 9 years, excluding the potential effect of other macroeconomic shocks. Fourth, this paper will expand upon the findings of Raddatz "The Wrath of God: Macroeconomic Costs of Natural Disasters', to look at how different types of disasters behave differently.

The next section will discuss the state of current literature for studies related to natural disasters and economics. The following section describes the data and the main variables of investigation. This is then followed by a quick discussion of the methodology used to find the desired results, which is shortly followed with the actual models and findings, including robustness checks. The paper then concludes with a summarization of the findings, limitations, and next steps within the conclusion.

Literature Review

Overview

With the increasing concern about climate change, many sources suggest that there will be an increase in the frequency of extreme weather events.[1] It may be in the near future that natural disasters become the normality. The rise of economic studies looking at the economic impact of natural disasters is a relatively new branch of research, with most papers predominantly being developed in the twenty-first century. [2] Existing literature can be split into three different fields of economics: micro-econometric studies looking at the household ability to cope with disasters, case studies regarding specific disasters and sectoral losses, and the macroeconomic impact of natural disasters. [3]

While varying in methodology and scope of the study, most macroeconomic literature can be split into looking at either the direct impact or indirect impact caused by natural disasters. The direct impact of natural disasters can be defined as the immediate damages a natural disaster causes on society through loss of life, destruction of physical capital, displacing population, and disruption of economic activity.[4] Indirect impact refers to the economic activity that is unable to take place due to the aftereffects of the natural disasters, potentially consequences of the direct damage done, and also referring to the additional costs incurred for needing to substitute to inferior or temporary methods while the typical methods of productions are unavailable.[5] There is more consensus within the literature regarding the strong negative impact that natural disasters cause through direct damages, which is quite unclear within indirect damages. The probability of finding a significant negative effect of natural disasters on the economy is 73% for direct costs and 43% for indirect costs. [6] In fact, indirect costs have a 62% probability of reporting insignificant disaster outcomes.[7] Indirect damages are also much harder to measure, as they can occur with both a delay in time and can be difficult to distinguish from other macroeconomic

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[1] P. A. Raschky, "Institutions and the Losses from Natural Disasters," *Natural Hazards and Earth System Sciences* 8, no. 4 (2008): 627–34, https://doi.org/10.5194/nhess-8-627-2008.P627

[2] Sara Lazzaroni and Peter A.G. van Bergeijk, "Natural Disasters' Impact, Factors of Resilience and Development: A Meta-Analysis of the Macroeconomic Literature," *Ecological Economics* 107 (2014): 333–46, https://doi.org/10.1016/j.ecolecon.2014.08.015., P333

[3] Sara Lazzaroni and Peter A.G. van Bergeijk, "Natural Disasters' Impact, Factors of Resilience and Development: A Meta-Analysis of the Macroeconomic Literature," *Ecological Economics* 107 (2014): 333–46, https://doi.org/10.1016/j.ecolecon.2014.08.015., P333

[4] Tatyana Deryugina, "Economic Effects of Natural Disasters," *IZA World of Labor*, 2022, https://doi.org/10.15185/izawol.493., P2

[5] Eduardo A. Cavallo and Ilan Noy, "The Economics of Natural Disasters: A Survey," *SSRN Electronic Journal*, 2009, https://doi.org/10.2139/ssrn.1817217., P8.

[6] Peter A. G. van Bergeijk and Sara Lazzaroni, "Macroeconomics of Natural Disasters: Strengths and Weaknesses of Meta-Analysis versus Review of Literature," *Risk Analysis* 35, no. 6 (2015): 1050–72, https://doi.org/10.1111/risa.12372., P1062

[7] Sara Lazzaroni and Peter A.G. van Bergeijk, "Natural Disasters' Impact, Factors of Resilience and Development: A Meta-Analysis of the Macroeconomic Literature," *Ecological Economics* 107 (2014): 333–46, https://doi.org/10.1016/j.ecolecon.2014.08.015.P342.

shocks, leading to an overall underestimation when calculated in total disaster costs.[8] The indirect damages attributed to natural disasters is both one that is harder to quantify but also of more interest for this paper and policymakers.

Indirect studies generally include variables for geographical location, time-based characteristics, objective disaster variables, disaster type, and a macroeconomic measure in a panel format. Justification for using panel data is the ability to include location-fixed effects, controlling for time-invariant unobserved determinants that are hard to differentiate from the desired indirect damages measurement.[9] Raddatz finds within his VAR modelling those climatic disasters (including climate-related, hydrological, and meteorological disasters as classified in the EM-DAT database) have an on average negative impact on per capita GDP, while geological events have an insignificant positive impact.[10] In a meta-analysis study done by Klomp and Valcx, they find only a short-run impact for climatological and geological disasters, while hydrological and meteorological had a negative impact in both the short and long run for economic growth per capita.[11] Within natural disasters themselves, there seems to be an identified heterogenous effect on the long run and short run economic outcomes.

The investigated time span for indirect damage studies can also be split further into short-run (several years) and long run (at least five years, but typically at least a decade). While looking at similar macroeconomic variables in both the short and long run, the literature finds different results. Indirect cost studies looking at a medium-term to long-term effect have around an 8 percentage point higher probability to be significantly positive and a 21% lower probability of being significantly negative.[12] Many natural disasters also have a moderate impact in the short run that disappears, with only more severe or frequent natural disasters causing long-term negative consequences.[13]The timing of the natural disaster also influences the resulting short-term outcome, as natural disasters occurring during periods of economic expansion tends to cause more negative effects than those happening during recessions.[14] Overall, existing research finds that results are contingent on multiple factors, such as disaster type, country, dependent variable, and disaster measure.

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[8] Hartwig De Haen and Günter Hemrich, "The Economics of Natural Disasters: Implications and Challenges for Food Security," *Agricultural Economics* 37 (2007): 31–45, https://doi.org/10.1111/j.1574-0862.2007.00233.x., P33.
[9] W. J. Botzen, Olivier Deschenes, and Mark Sanders, "The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies," *Review of Environmental Economics and Policy* 13, no. 2 (2019): 167–88, https://doi.org/10.1093/reep/rez004., P176.
[10] Claudio Raddatz, "The Wrath of God: Macroeconomic Costs of Natural Disasters," *Policy Research Working Papers*, 2009, https://doi.org/10.1596/1813-9450-5039., P9.
[11] Jeroen Klomp and Kay Valckx, "Natural Disasters and Economic Growth: A Meta-Analysis," *Global Environmental Change* 26 (2014): 183–95, https://doi.org/10.1016/j.gloenvcha.2014.02.006., P191.
[12] Peter A. G. van Bergeijk and Sara Lazzaroni, "Macroeconomics of Natural Disasters: Strengths and Weaknesses of Meta-Analysis versus Review of Literature," *Risk Analysis* 35, no. 6 (2015): 1050–72, https://doi.org/10.1111/risa.12372., P1065; Mark Skidmore and Hideki Toya, "Do Natural Disasters Promote Long-Run Growth?," *Economic Inquiry* 40, no. 4 (2002): 664–87, https://doi.org/10.1093/ei/40.4.664., P665.
[13] Carolyn Kousky, "Informing Climate Adaptation: A Review of the Economic Costs of Natural Disasters," *Energy Economics* 46 (2014): 576–92, https://doi.org/10.1016/j.eneco.2013.09.029. , P58.
[14] Mark Skidmore, "Risk, Natural Disasters, and Household Savings in a Life Cycle Model," *Japan and the World Economy* 13, no. 1 (2001): 15–34, https://doi.org/10.1016/s0922-1425(00)00056-6., P306.

Disaster Measures

Literature looking at the same variables can have varying outcomes depending on the measure used to account for natural disasters. The two general measures for disasters are frequency and intensity, with intensity predominantly being used. Indirect cost studies that use disaster intensity have a 10% more likely probability of reporting positive and significant results. [15] Nevertheless, a negative relationship can still be found using an intensity measure. Disaster intensity is often measured in terms of economic damages cost, leading to a higher correlation with GDP per capita. [16] Using the total damage incurred to GDP ratio measure for disaster intensity leads to a more significant relationship found than intensity measures that look at the share of the population affected. [17] When using the measure of the number of people affected, a decrease in GDP per capita growth rate is recorded. However, when using the death toll attributed to the natural disaster, the relationship disappears. [18] When intensity is measured by the physical intensity of the natural disaster, a strong, negative, insignificant relationship is found. [19] Alternatively, measuring the frequency of disasters leads to a positive correlation with growth for climatological disasters and a negative correlation for geophysical disasters. [20] For a better overview of the impact disasters have, some literature uses a combination of the existing measures for disaster magnitude. In particular, the paper closest to this paper, authored by Ilan Noy uses the three measures of the death toll, number of people affected, and amount of direct damage caused by the natural disaster. These measures are then standardized in order to measure the impact of the disaster relative to the size of the economy, with robustness tests validating that the approach did not insert any endogeneity.[21] Using the lag version of the dependent variable is a common practice within macroeconomic literature to eliminate the endogeneity introduced by disaster data with respect to economic growth.[22]

Commonly Used Dependent Variables

The most used dependent variable to investigate the indirect impact of natural disaster are GDP measures, with very few papers looking at other measures. Out of 2339 indirect cost papers, 80% of indirect cost studies focus on GDP and income, while education was investigated in only

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[15] Peter A. G. van Bergeijk and Sara Lazzaroni, "Macroeconomics of Natural Disasters: Strengths and Weaknesses of Meta-Analysis versus Review of Literature," *Risk Analysis* 35, no. 6 (2015): 1050–72, https://doi.org/10.1111/risa.12372., P1065

[16] W. J. Botzen, Olivier Deschenes, and Mark Sanders, "The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies," *Review of Environmental Economics and Policy* 13, no. 2 (2019): 167–88, https://doi.org/10.1093/reep/rez004., P176.

[17] Jeroen Klomp and Kay Valckx, "Natural Disasters and Economic Growth: A Meta-Analysis," *Global Environmental Change* 26 (2014): 183–95, https://doi.org/10.1016/j.gloenvcha.2014.02.006., P192

[18] Nourin Shabnam, "Natural Disasters and Economic Growth: A Review," *International Journal of Disaster Risk Science* 5, no. 2 (2014): 157–63, https://doi.org/10.1007/s13753-014-0022-5., P157.

[19] W. J. Botzen, Olivier Deschenes, and Mark Sanders, "The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies," *Review of Environmental Economics and Policy* 13, no. 2 (2019): 167–88, https://doi.org/10.1093/reep/rez004., P178.

[20] Sara Lazzaroni and Peter A.G. van Bergeijk, "Natural Disasters' Impact, Factors of Resilience and Development: A Meta-Analysis of the Macroeconomic Literature," *Ecological Economics* 107 (2014): 333–46, https://doi.org/10.1016/j.ecolecon.2014.08.015., P334

[21] Ilan Noy, "The Macroeconomic Consequences of Disasters," *Journal of Development Economics* 88, no. 2 (2009): 221–31, https://doi.org/10.1016/j.jdeveco.2008.02.005., P222-224

[22] Xianhua Wu and Ji Guo, "Natural Disasters and Economic Growth—an Empirical Study Using Provincial Panel Data of China," *Sustainability*, December 19, 2015, 81–104, https://doi.org/10.1007/978-981-16-1319-7_3., P16791.

13%.[23] These measures of GDP vary from measuring economic performance by the level of real GDP, to the standards of living through the usage of real GDP per capita and the growth over time. The role of investment, openness, population, and institution quality, which are underinvestigated measures as dependent variables, are commonly included used as control variables instead, particularly in the regards of cross-country studies[24].

Debate

Within the plethora of literature focusing on the growth rate of GDP per capita, there is still much debate on the actual indirect costs impact of natural disasters. While, on average, natural disasters have a negative impact on short-run economic growth, the result widely depends on the location of the study and the type of natural disaster. Higher income, better education, more investment, and higher quality institutions lead to smaller negative effects. [25]A median reduction of 2 percentage points is found for the same year real GDP as the disaster occurrence, but much literature finds insignificant results or even a positive result. [26]

While there has been some justification for the results why natural disasters can have a positive impact, overall, there is still weak evidence. It is proposed that natural disasters can cause a growth in GDP through a process of creation destruction, where suboptimal infrastructure is destroyed and allows the economy to replace it with a better version.[27] While this explanation may hold in the event of the impact of a single occurring disaster, it seems less effective in explaining the difference in areas that are more natural disasters-prone, which constantly experiences such destruction. A second explanation is that the destruction of infrastructure is not captured by GDP, while the activity done to replace infrastructure and capital goods is accounted, potentially accounting for the recorded growth. [28] While this may work in considering the total GDP output, it does not seem to make sense when we look at GDP per capita, the standards of living which should not change by this proposed explanation. Finally, In a theoretical paper proposed by Strulik and Trimborn, they predicted insignificant responses in GDP when disasters destroy both durable and productive capital, with a negative response expected when productive capital is the main type of goods that are destroyed. [29] Positive effects

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[23] Sara Lazzaroni and Peter A.G. van Bergeijk, "Natural Disasters' Impact, Factors of Resilience and Development: A Meta-Analysis of the Macroeconomic Literature," *Ecological Economics* 107 (2014): 333–46, https://doi.org/10.1016/j.ecolecon.2014.08.015., PP. 339, 344

[24] P. A. Raschky, "Institutions and the Losses from Natural Disasters," *Natural Hazards and Earth System Sciences* 8, no. 4 (2008): 627–34, https://doi.org/10.5194/nhess-8-627-2008., P176; Noy, Ilan & Cavallo, Eduardo. (2010). The Aftermath of Natural Disasters: Beyond Destruction. CESifo Forum. 11. 25-35., P30.

[25] Carolyn Kousky, "Informing Climate Adaptation: A Review of the Economic Costs of Natural Disasters," *Energy Economics* 46 (2014): 576–92, https://doi.org/10.1016/j.eneco.2013.09.029., P58.; Xianhua Wu and Ji Guo, "Natural Disasters and Economic Growth—an Empirical Study Using Provincial Panel Data of China," *Sustainability*, December 19, 2015, 81–104, https://doi.org/10.1007/978-981-16-1319-7_3., P16791.

[26] Jeroen Klomp and Kay Valckx, "Natural Disasters and Economic Growth: A Meta-Analysis," *Global Environmental Change* 26 (2014): 183–95, https://doi.org/10.1016/j.gloenvcha.2014.02.006., P183.

[27] Tatyana Deryugina, "Economic Effects of Natural Disasters," *IZA World of Labor*, 2022, https://doi.org/10.15185/izawol.493., P2.

[28] Mark Skidmore and Hideki Toya, "Do Natural Disasters Promote Long-Run Growth?," *Economic Inquiry* 40, no. 4 (2002): 664–87, https://doi.org/10.1093/ei/40.4.664., P665; Derek Kellenberg and A. Mushfiq Mobarak, "The Economics of Natural Disasters," *Annual Review of Resource Economics* 3, no. 1 (2011): 297–312, https://doi.org/10.1146/annurev-resource-073009-104211., P302.

[29] Holger Strulik and Timo Trimborn, "Natural Disasters and Macroeconomic Performance," *Environmental and Resource Economics* 72, no. 4 (2018): 1069–98, https://doi.org/10.1007/s10640-018-0239-7., P1069.

can also be attributed to better preparedness and mitigation for disasters, foreign instance, insurance and reinsurance, and measurement error by the underestimation of total damages in data. [30]

Data

The data regarding natural disasters and their impacts is collected in the Emergency event Database (EM-DAT), also known as International Disaster Database, which was created by the Centre for Research on the Epidemiology of Disasters. It contains data about natural disasters that occurred from 1900 to 2023, recording disasters that either caused 10 fatalities, affected 100 people, led to a declaration of state of emergency, or a call for international assistance.[31] Disasters are first classified by their type (natural or technological) with more specific subtypes (hydrological, meteorological, geophysical, and climatological). The subtypes of hydrological, meteorological, and climatological are often bundled as one category called "climatological" within the current literature, but is treated separately in EM-DAT. Within the investigated time of this study, there was only one geophysical event, which its small sample leads to its exclusion in the latter exploration of the difference in impact for specific disaster types. A map of the number of incidences of natural disasters over the periods for the overall category and specific subtypes can be found in **Appendix Figure 1-5**, with a simple breakdown illustrated in **Figure 1.**

In terms of measures of natural disaster impact existing within EM-DAT, the direct human and economic losses are recorded, with no measure of indirect impact. There has been concerns expressed in literature regarding the accuracy of the information, as there is a tendency for developed countries to have better data quality and hence higher reported damages.[32] In response to this and the fact that many disasters do not have damages documented, these measures are not taken into consideration when creating a natural disaster measure within this paper. Instead, two measures are created to measure the severity of natural disasters at the state level: frequency and duration. The basic summary statistics of mean, standard deviation, minimum, and maximum are provided in **Appendix Table 2** for all used variables, with the detailed breakdown of frequency by disaster type in **Appendix Table 3**.

Figure 1

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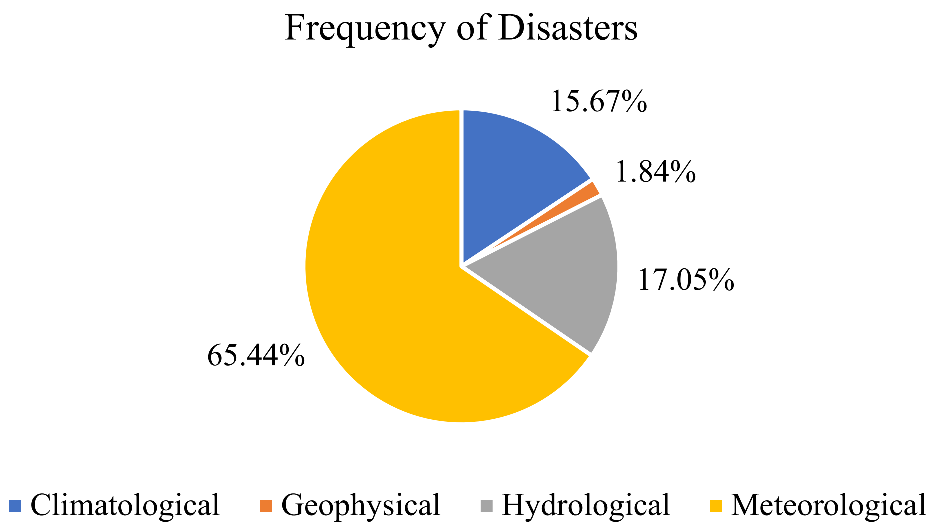
[30] Sara Lazzaroni and Peter A.G. van Bergeijk, "Natural Disasters' Impact, Factors of Resilience and Development: A Meta-Analysis of the Macroeconomic Literature," *Ecological Economics* 107 (2014): 333–46, https://doi.org/10.1016/j.ecolecon.2014.08.015., P344

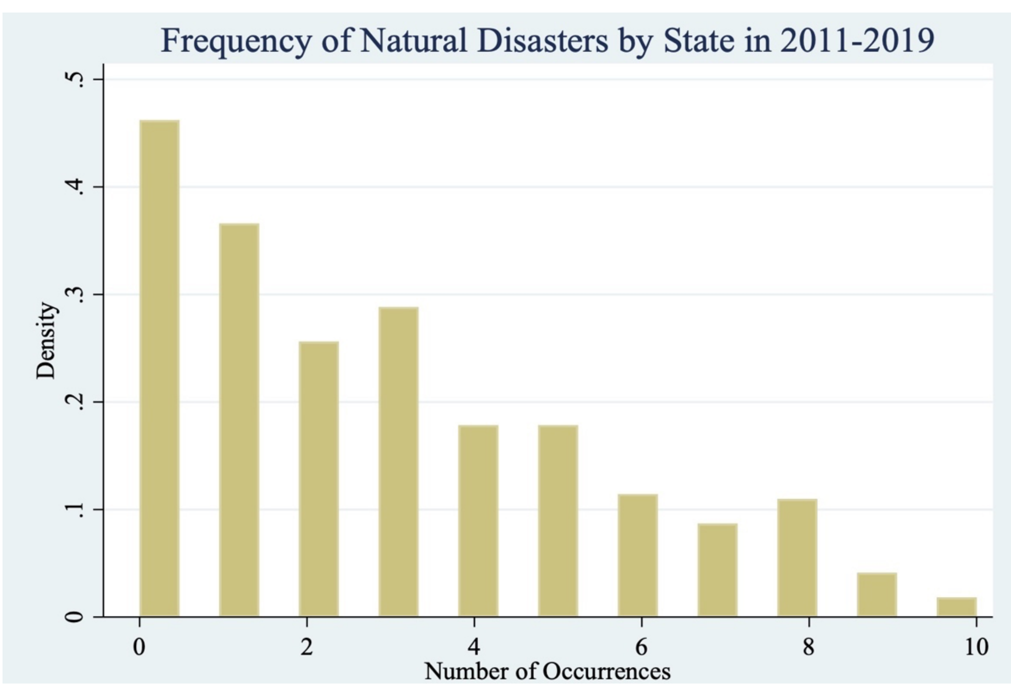
[31] EM-DAT, "EM-DAT Guidelines: Data Entry, Field Description/Definition," EM-DAT Public, accessed July 28, 2023, https://public.emdat.be/about.

[32] Xianhua Wu and Ji Guo, "Natural Disasters and Economic Growth—an Empirical Study Using Provincial Panel Data of China," *Sustainability*, December 19, 2015, 81–104, https://doi.org/10.1007/978-981-16-1319-7_3., P16796; P. A. Raschky, "Institutions and the Losses from Natural Disasters," *Natural Hazards and Earth System Sciences* 8, no. 4 (2008): 627–34, https://doi.org/10.5194/nhess-8-627-2008., P631; Ilan Noy, "The Macroeconomic Consequences of Disasters," *Journal of Development Economics* 88, no. 2 (2009): 221–31, https://doi.org/10.1016/j.jdeveco.2008.02.005., P224.



Frequency records the number of natural disasters that occur within the state for a current year. As EM-DAT data is recorded at the disaster-level, records were aggregated based on location information to accumulate a count per state. **Figure 2,** shows that the frequency of natural disasters would take place differs widely in states, with most states having only a few disasters per year. The measure of frequency is unable to reflect the intensity of any specific event, which is hence not the aim of this paper. Instead, this paper will aim to see the lasting impact that natural disasters can have in the economy, seeing whether the indirect damages can persist and influence the standards of living.

Figure 2



The measure of duration is one that is uniquely proposed within this paper, and unseen in most of the existing literature. Duration measures the number of unique days within a year that a state is experiencing a natural disaster, calculated based on the start and end date recorded within EM-DAT. It is then standardized by dividing by the number of days within a year, 365, for better interpretation of the results. The usage of duration provides an understanding of how states that are constantly under the influence of natural disasters may differ from those who experience a short-term event.

Data on real GDP comes from the Bureau of Economic Analysis, with real GDP per capita calculated by a division of the local population. Other control variables such as percentage of bachelor graduates, labor force, government expenditure, and effective exchange rate come from sources such as the National Center for Education Statistics, US Census Bureau, and the U.S. Bureau of Labor Statistics. A detailed breakdown of variables, their descriptions, and source can be found within **Appendix Table 1**. Due to data availability constraints for publicly available data at the state level, some of the commonly used macroeconomic growth literature control variables are not used, such as domestic credit and institutional strength. Moreover, to eliminate the potential impact caused by other macroeconomic events, the years covered is limited from 2011 to 2019, avoiding the impact of the 2009 Great Recession and 2020 COVID pandemic. Overall, the panel covers 2011-2019 for the 50 states and District of Columbia for the United States.

Methodology

The main goal is to describe the macroeconomic outcomes impacted by natural disasters. Therefore, an investigation is done on both real GDP growth rate and real GDP per capita growth rate, to reflect standards of living and economic performance of the state. This is done by starting with the basic model:

$$y_{i,t} = \alpha_i + \beta_1 y_{i,t-1} + \beta_2 ND_{i,t} + \varphi X_i + \varepsilon_{it}$$

Where $y_{i,t}$ is the annual real GDP per capita growth rate, $ND_{i,t}$ is the measure for natural disaster, and X_i are the control variables. A real GDP per capita growth rate lag variable $y_{i,t-1}$ is introduced, following the general specifications in literature to help eliminate the endogeneity natural disaster has upon economic performance.[33] Then, to better control for unobserved heterogeneity, individual fixed effects and time fixed effects are included, resulting in the fixed effects model:

$$y_{i,t} = \alpha_i + \beta_1 y_{i,t-1} + \beta_2 ND_{i,t} + \varphi X_i + \gamma_i + \delta_t + \varepsilon_{it}$$

Where γ_i represents state fixed effects, capturing time-invariant characteristics for each state I and δ_t represents time fixed effects, capturing unobserved time-specific effects across all states at time t.

All independent and dependent variables that were not standardized had the application of natural log to allow interpretations of the regression coefficient as elasticities, and better

[33] Xianhua Wu and Ji Guo, "Natural Disasters and Economic Growth—an Empirical Study Using Provincial Panel Data of China," *Sustainability*, December 19, 2015, 81–104, https://doi.org/10.1007/978-981-16-1319-7_3., P16794.

comparability between the different coefficients. [34] These transformations are indicated with the prefix "ln" in the name of the variables. All lag terms are indicated with the prefix "L". The disaster measure is assumed to be exogenous, following the typical and uncontroversial assumptions made in past literature. As natural disasters are something that cannot be manually triggered, it is quite safe to assume that the exogenous assumption is valid. An additional investigation is done to see the differences between the effects of different types of natural disasters using the final specified model with all control variables. A robustness check is then done on the final models using GMM to confirm results.

Results

Baseline results are presented in **Table 1**, without any control variables. Frequency plays a positive and significant impact on the real GDP capita growth rate and real GDP growth rate, with and without considering the impact of the duration of natural disaster-affected days. This is quite surprising, as the expectation would be that states experiencing higher frequency of natural disasters would suffer more in terms of standards of living and economic performance by the destruction it brings. There is only an insignificant negative impact played by standardized duration. It could be that the results are driven by uncontrolled variables or omitted variable bias, as no controls are added yet. It seems that the number of natural disasters, or in other words, the number of shocks is much more important.

Table 1

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	RCAPITAG	RCAPITAG	RCAPITAG	RGDPG	RGDPG	RGDPG
ln_frequency	0.00538***		0.00556***	0.00446***		0.00462***
ln_duration		-0.000558	-0.000735		-0.000501	-0.000646
L_RCAPITAG	-0.0409	-0.0227	-0.0371			
L_RGDPG				0.0341	0.0502	0.0372
Constant	-0.00158	-0.000127	-0.00414	0.00491**	0.00586**	0.00265
Observations	408	408	408	408	408	408
Adjusted R-squared	0.530	0.519	0.531	0.516	0.508	0.517
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Then, state-level and time fixed effects are added to control for unobserved heterogeneity across states and time in **Table 2**. Even after adding the control variables, the positive and significant effect for frequency persists for both real GDP per capita growth rate and real GDP growth.

[34] P. A. Raschky, "Institutions and the Losses from Natural Disasters," *Natural Hazards and Earth System Sciences* 8, no. 4 (2008): 627–34, https://doi.org/10.5194/nhess-8-627-2008., P632.

Table 2

Variables	(1) RCAPITAG	(2) RCAPITAG	(3) RCAPITAG	(4) RGDPG	(5) RGDPG	(6) RGDPG
ln_frequency	0.00678***		0.00664***	0.00539***		0.00540***
ln_duration		-0.000860	-0.000378		-0.000345	4.54e-05
L_RCAPITAG	0.0484	0.0501	0.0481			
L_RGDPG				0.253***	0.251***	0.253***
Constant	-0.000856	0.00242	-0.00167	0.00285	0.00634***	0.00295
Observations	408	408	408	408	408	408

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

To breakdown the effects further from other potential influencing factors, an investigation is done into the specific factors that influences real GDP per capita and real GDP growth rate to see some possible influencing factors in **Table 3**. The included variables are ones typical within macroeconomic growth literature, with effective exchange rate included as well on the national level to control for the influence of trade. However, as it did not vary between states, it is omitted from the table. Even after all the controls, the coefficient is quite consistent throughout the different iterations of the model, all being around 0.004 to 0.005 for the frequency on both real GDP per capita and real GDP growth rate.

Table 3

VARIABLES	(1) RCAPITAG	(2) RCAPITAG	(3) RCAPITAG	(4) RGDPG	(5) RGDPG	(6) RGDPG
ln_frequency	0.00517***		0.00534***	0.00412**		0.00425**
ln_duration		-0.000575	-0.000731		-0.000458	-0.000582
L_CAPITAG	-0.0539	-0.0372	-0.0510			
L_RGDPG				0.0146	0.0280	0.0166
GOVEXPG	-0.00143	0.0110	0.00106	-0.000597	0.00914	0.00136
LABORG	0.221*	0.237*	0.219*	0.313***	0.325***	0.311***
BACHELOR	0.000394	0.000266	0.000594	-0.000305	-0.000414	-0.000146
Constant	-0.0129	-0.00827	-0.0213	0.0141	0.0179	0.00744
Observations	408	408	408	408	408	408
Adjusted R-squared	0.534	0.525	0.535	0.530	0.523	0.530
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Disaster Type Specifications

When breaking down the impact by disaster type, the result of frequency is quite different from the overarching results as shown in **Table 4.** Climatological natural disaster frequencies play an insignificant positive role. This differs from much literature, which found that climatological natural disasters play a significant negative role. Hydrological events, in fact, play a significant negative impact. As studies in literature often lump climatological, hydrological, and meteorological events as one category of climate-related disasters, this provides some validation for the results found of hydrological.[35] For meteorological disasters, however, there is a positive significant effect. This is much closer to the results and coefficients obtained in the basic model. Considering that 65% of the natural disaster within the data is classified as meteorological, this provides some explanation of how the positive results was found. Overall, heterogenous effect depending on disaster types demonstrates that it may be hard to classify the total effects of natural disasters as one single event, but rather needs more specific investigation.

Table 4

[35]Claudio Raddatz, "The Wrath of God: Macroeconomic Costs of Natural Disasters," *Policy Research Working Papers*, 2009, https://doi.org/10.1596/1813-9450-5039., P9.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	RCAPITAG	RCAPITAG	RCAPITAG	RGDPG	RGDPG	RGDPG
ln_frequency_climate	0.00375			0.00473		
ln_frequency_hydro		-0.0102***			-0.00626*	
ln_frequency_meteor			0.00566***			0.00428**
L_RCAPITAG	-0.0448	-0.0413	-0.0515			
L_RGDPG				0.0203	0.0253	0.0170
GOVEXPG	0.00878	0.00884	-0.00201	0.00742	0.00742	-0.000666
LABORG	0.234*	0.235*	0.223*	0.320***	0.324***	0.314***
BACHELOR	0.000136	7.77e-05	0.000442	-0.000507	-0.000557	-0.000281
Constant	-0.00308	-0.000807	-0.0135	0.0215	0.0237	0.0141
Observations	408	408	408	408	408	408
Number of state1	51	51	51	51	51	51
Adjusted R-squared	0.524	0.524	0.535	0.523	0.523	0.530
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

*** p<0.01, ** p<0.05, * p<0.1

Robustness Check

Two robustness checks are done using the Generalized Methods of Movements. As the dynamic panel model includes a lagged dependent variable, it is inevitably biased. The Generalized Methods of Movements (GMM) proposed by Arellano-Bover and Blundell-Bond in the 1990s. GMM allows for the examination of the effect of the lag dependent variable on the current dependent variable, and investigate bias caused by mismeasurement. Two specifications are done to investigate the full model results, one validating the results of **Table 3,** and one validating the results of **Table 4.**

Following best practices for panel datas with many individuals and fewer time periods, a two-step system GMM is used.[36] As normal specifications led to a Hansen-J p-value of 1.0, this indicated that there were too many instruments included, so a collapse function was applied to get the current results. The AR(1) specification is still supported, demonstrated by the significant p-value.

Within the GMM model of **Table 5**, where the full model for all natural disasters type with all control variables is tested, results are quite different from what the fixed effects regression model provided. Frequency is now insignificant for both real GDP per capita growth rate and real GDP growth rate. In fact, the sign switches from positive to negative for real GDP growth rate results.

Table 5

Variables	(1) RCAPITAG	(2) RGDPG
ln_frequency	0.00291	-0.00212
ln_duration	-0.000508	-0.000108
L_RCAPITAG	0.0958	
L_RGDPG		0.0867
GOVEXPG	-0.0444	-0.0670
LABORG	-0.469	-0.265
BACHELOR	0.000579	-0.00428
Constant	-0.00386	0.157
	(0.183)	(0.342)
Observations	408	408
No. of instruments	26	26
AR1 (p-value)	0.0128	0.0295
AR2 (p-value)	0.215	0.0852
Hansen-J (p-value)	0.121	0.500

* p<0.10, ** p<0.05, *** p<0.010

Similarly, the GMM model results in insignificant coefficients for each disaster type as well in **Table 6.** The observed positive and negative relationship, as it is insignificant overall, demonstrates that there is no conclusion that can be made. It seems that after the bias correction done by GMM, there is no real evidence of any relationship. As the results found were insignificant, the results found in the fixed effect regression model is not robust.

[36] David Roodman, "How to Do Xtabond2: An Introduction to Difference and System GMM in Stata," *The Stata Journal: Promoting Communications on Statistics and Stata* 9, no. 1 (2009): 86–136, https://doi.org/10.1177/1536867x0900900106.

Table 6

Variables	(1) RCAPITAG	(2) RCAPITAG	(3) RCAPITAG	(4) RGDPG	(5) RGDPG	(6) RGDPG
ln_frequency_climate	0.00148	0.00261				
ln_frequency_hydro			-0.00690	0.00662		
ln_frequency_meteor					0.00380	0.00278
ln_duration	-0.000380	-0.000426	-0.000316	-0.000151	-0.000561	-0.000231
L_RCAPITAG	0.106		0.105		0.0998	
L_RGDPG		0.0698		0.0732		0.0757
GOVEXPG	-0.0122	-0.0946	-0.0274	-0.105	-0.0591	-0.109
LABORG	-0.583	0.0484	-0.617	0.0205	-0.460	-0.00658
BACHELOR	0.000358	0.000591	0.000306	0.000754	0.00135	0.0000727
Constant	0.00606	-0.00356	0.00911	-0.00426	-0.0272	0.0206
Observations	408	408	408	408	408	408
No. of instruments	26	26	26	26	26	26
AR1 (p-value)	0.0126	0.00654	0.0190	0.00547	0.0123	0.00283
AR2 (p-value)	0.250	0.0779	0.229	0.0905	0.203	0.108
Hansen-J (p-value)	0.109	0.157	0.141	0.0927	0.112	0.207

* p<0.10, ** p<0.05, *** p<0.010

Conclusion

The results are inconclusive. There is no significant relationship that is robust for the frequency of natural disasters and the growth of real GDP or growth of real GDP per capita. While there are interesting relationships found varying by disaster type, these findings did not hold up to the GMM model so no relationships can be confirmed. Instead of providing evidence towards one side of the debate within the current literature, this study finds itself joining the other 62% of indirect cost study papers of having insignificant results.

Limitations

There are a couple of limitations that may have impacted the results of this study. First, the data used within this study is quite limited. As the panel sampled was not big, this could have influenced the probability of finding significant results, particularly as adjusting for bias requires better information. Second, all natural disasters of different intensities were treated equivalently within this study due to limitations of data. Many disasters within the EM-DAT data lack damages information, which would require imputation and separate data gathering that is beyond the scope of this study. Including intensity information in addition to the frequency measure may reveal more conclusive results, allowing disasters of similar sizes to be treated similarly within the results. Third, not all common macroeconomic growth literature variables were available at the state level. It is possible if more controls were put in place, that the impact of solely the natural disaster measure itself would be better isolated with less bias, and more robust results. The lack of data also inhibited the types of models that could be fit or tried.

The impact of natural disasters on the economy is a field full of potential for more investigations, with much more that can possibly be done with the explorations within this study. First, the impact of the proposed natural disaster measures on other macroeconomic variables, such as human capital, is a simple extension that would add to an underinvestigated field within the current literature. Altering the time frame of the study to either be even shorter or longer would allow for better comparability with existing literature on short-term and long-term results. Looking at county-level data would also guarantee a larger dataset that would entertain more investigations. Finally, a look at an even more detailed disaster level could provide better insight into how different events impact the economy differently.

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Appendix

Table A1. Description of Variables

Abbreviation	**Variable**	**Source**
EXCHANGEG	Real effective exchange rate	world bank
BACHELOR	Bachelor degree completion	National Center for Educational Statistics
GOVEXPG	Total government expenditure	United States Census Bureau
RGDPG	Growth in real GDP	Bureau of Economic Analysis
RCAPITAG	Growth in RGDP per capita	Bureau of Economic Analysis and United StatesCensus Bureau
LABORG	Labor growth	US Bureau of Labor Statistics
Frequency	Frequency of natural disasters per year	EM-DAT
Duration	Duration of natural disaster occurrences per year	EM-DAT
frequency_hydro	Frequency of hydrological disasters per year	EM-DAT
frequency_meteor	Frequency of meteorological disasters per year	EM-DAT
frequency_climate	Frequency of climatological disasters per year	EM-DAT

Table A2. Average for Variables by State

	frequency	standard duration	CAPITA G	RGDP G	EXCHANGE G	DEFLATOR G	BACH ELOR	LABOR G	GOVEX PG
Alabama	4.111	.053	0.002	.007	.025	.018	24.254	.003	.048
Alaska	.111	.001	-0.011	-.009	.025	-.003	28.967	-.005	.011
Arizona	.444	.01	0.012	.023	.025	.02	28.24	.014	.063
Arkansas	4.222	.061	0.007	.009	.025	.017	21.907	-.001	.044
California	.889	.014	0.024	.029	.025	.016	32.489	.003	.064
Colorado	3.556	.043	0.016	.03	.025	.013	39.503	.014	.06
Connecticut	2.444	.033	-0.001	-.001	.025	.021	38.249	-.002	.035
Delaware	1.667	.018	-0.010	0	.025	.025	30.937	.01	.066
District of Columbia	.889	.019	0.002	.01	.025	.021	56.381	.011	.083
Florida	2.444	.027	0.009	.023	.025	.021	28.357	.01	.049
Georgia	4.333	.054	0.012	.022	.025	.02	29.912	.008	.054
Hawaii	0	0	-0.005	0	.025	.021	31.811	.001	.053
Idaho	.444	.01	0.011	.029	.025	.018	26.554	.019	.056
Illinois	5.556	.193	0.005	.004	.025	.02	33.342	-.004	.058
Indiana	4.667	.169	0.006	.01	.025	.018	25.137	.005	.051
Iowa	4.333	.072	0.009	.013	.025	.019	27.77	0	.052
Kansas	5.667	.184	0.012	.014	.025	.015	32.03	0	.052
Kentucky	4	.172	0.004	.008	.025	.018	23.154	-.002	.05
Louisiana	3.778	.045	-0.009	-.008	.025	.01	23.167	-.001	.03
Maine	2.111	.027	0.009	.012	.025	.021	30.193	-.004	.044
Maryland	3.222	.04	0.001	.007	.025	.019	38.818	.005	.061
Massachusetts	2.667	.033	0.010	.016	.025	.02	41.962	.008	.061
Michigan	3.889	.05	0.007	.009	.025	.019	27.925	.005	.057
Minnesota	4	.059	0.005	.013	.025	.018	34.721	.007	.061
Mississippi	4.778	.073	0.003	.002	.025	.018	21.322	-.008	.037
Missouri	5.778	.197	0.003	.006	.025	.02	28.026	0	.047
Montana	1.778	.04	0.003	.012	.025	.015	30.11	.009	.039
Nebraska	3.778	.156	0.009	.016	.025	.018	30.942	.005	.048
Nevada	.556	.069	-0.002	.013	.025	.021	23.713	.012	.071
New Hampshire	2	.026	0.008	.013	.025	.019	35.96	.004	.051
New Jersey	3.222	.043	0.001	.006	.025	.019	38.129	.002	.056
New Mexico	2.333	.027	0.004	.006	.025	.008	26.836	.001	.043
New York	4.222	.056	0.010	.013	.025	.025	35.256	.001	.05
North Carolina	4	.052	0.006	.015	.025	.022	29.608	.004	.05
North Dakota	2.667	.047	0.015	.03	.025	.004	28.465	.006	.048
Ohio	4.667	.164	0.008	.011	.025	.019	27.03	0	.045
Oklahoma	4.778	.17	0.012	.017	.025	-.001	24.856	.005	.02
Oregon	.333	.008	0.014	.025	.025	.018	31.915	.006	.077
Pennsylvania	3.111	.041	0.006	.008	.025	.016	29.886	.002	.052
Rhode Island	1.889	.025	-0.004	.001	.025	.021	32.841	.002	.049
South Carolina	3.444	.045	0.008	.019	.025	.021	26.781	.007	.051
South Dakota	2.778	.048	0.002	.011	.025	.021	27.611	.005	.05
Tennessee	3.556	.055	0.009	.018	.025	.021	25.995	.007	.045
Texas	5.667	.188	0.014	.029	.025	.004	28.524	.012	.042
Utah	.333	.004	0.018	.035	.025	.018	32.385	.023	.067
Vermont	1.556	.021	-0.002	0	.025	.02	36.872	-.006	.05
Virginia	4.111	.056	0.001	.008	.025	.019	37.444	.004	.061
Washington	.444	.005	0.023	.037	.025	.017	34.203	.015	.065

West Virginia	1.333	.014	0.004	0	.025	.011	19.885	-.004	.039
Wisconsin	3.444	.044	0.005	.008	.025	.02	28.955	.001	.038
Wyoming	1.556	.02	-0.012	-.01	.025	.001	26.688	-.003	.014

Table A3. Average Frequency by Disaster Type

	FREQ_HYDRO	FREQ_METEOR	FREQ_CLIMATE
Alabama	.222	3.889	0
Alaska	0	.111	0
Arizona	0	.111	.333
Arkansas	.667	3.556	0
California	0	.556	.333
Colorado	.222	3.222	.111
Connecticut	.111	2.333	0
Delaware	.111	1.556	0
District of Columbia	0	.889	0
Florida	0	2.444	0
Georgia	.111	4.222	0
Hawaii	0	0	0
Idaho	0	.222	.222
Illinois	.667	4.667	.222
Indiana	.333	4.111	.222
Iowa	.556	3.556	.222
Kansas	.556	4.778	.333
Kentucky	.333	3.667	0
Louisiana	.222	3.556	0
Maine	.111	2	0
Maryland	0	3.222	0
Massachusetts	.111	2.556	0
Michigan	.333	3.333	.222
Minnesota	.444	3.222	.333
Mississippi	.444	4.333	0
Missouri	.778	4.778	.222
Montana	.111	1.444	.222
Nebraska	.222	3.333	.222
Nevada	0	.222	.333
New Hampshire	.111	1.889	0
New Jersey	.111	3.111	0
New Mexico	0	2.111	.222
New York	.111	4.111	0
North Carolina	0	4	0
North Dakota	.333	2.111	.222
Ohio	.333	4.111	.222
Oklahoma	.222	4.222	.333
Oregon	0	.111	.222
Pennsylvania	.111	3	0
Rhode Island	.111	1.778	0
South Carolina	.111	3.333	0

South Dakota	.333	2.222	.222
Tennessee	.333	3.222	0
Texas	.333	5	.333
Utah	0	.222	.111
Vermont	.111	1.444	0
Virginia	0	4.111	0
Washington	0	.333	.111
West Virginia	0	1.333	0
Wisconsin	.333	3	.111
Wyoming	0	1.556	0

Figure A1. Total Number of Natural Disaster Incidences in the US from 2011-2019

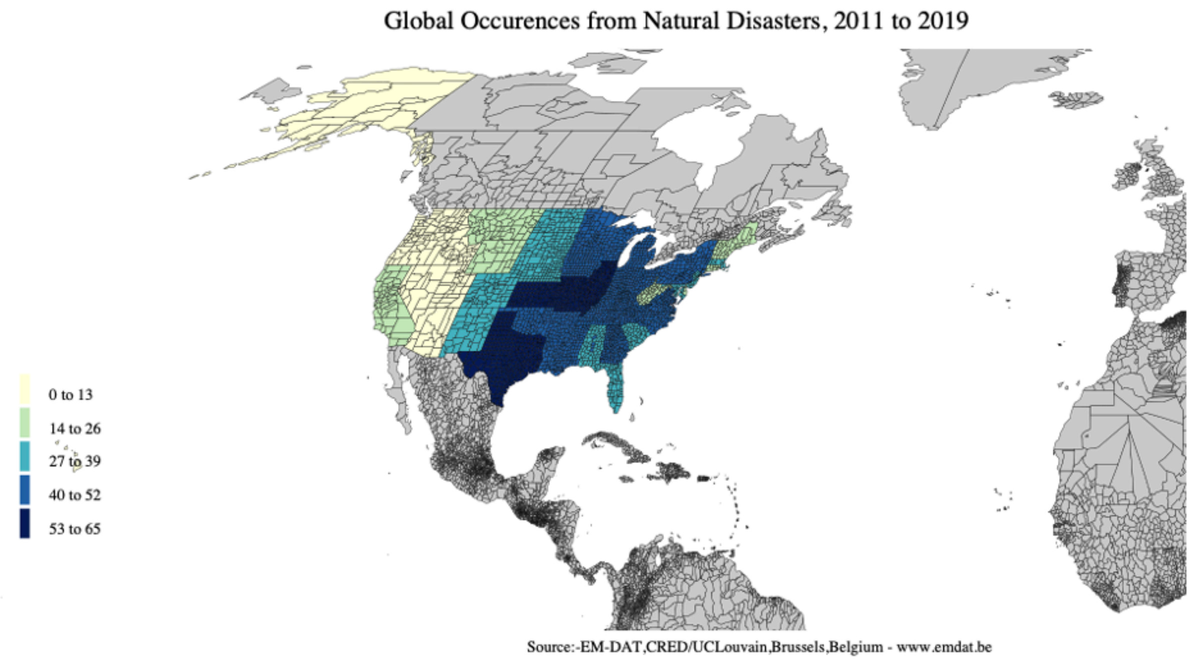

Figure A2. Total Number of Hydrological Incidences in the US from 2011-2019

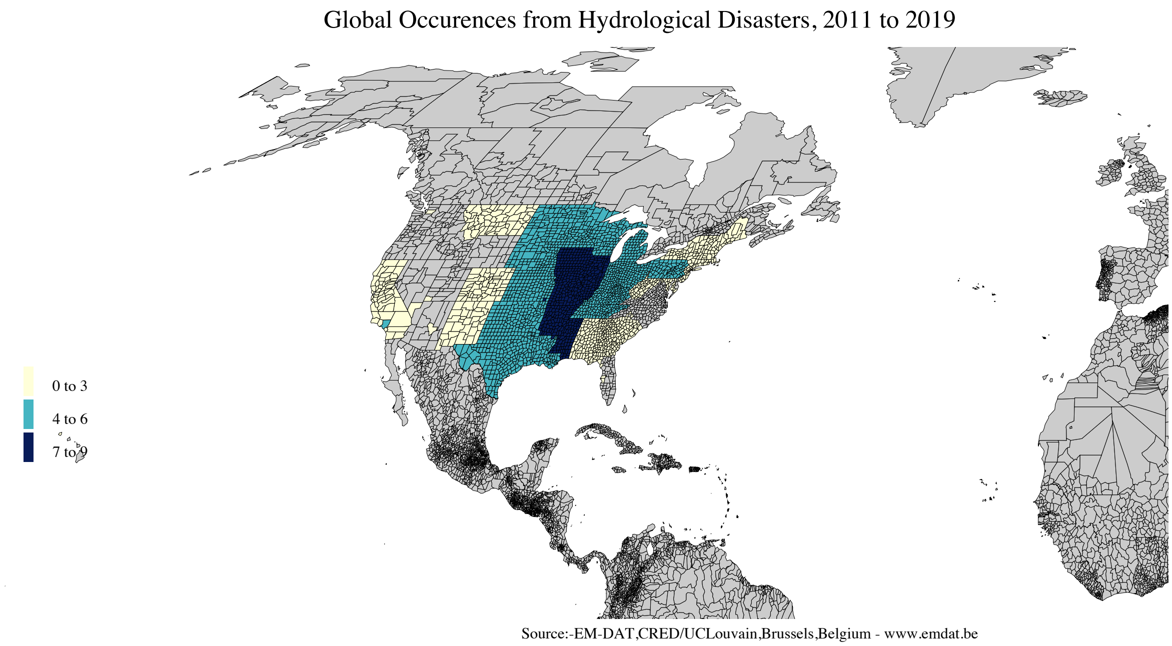

Figure A3. Total Number of Meteorological Disaster Incidences in the US from 2011-2019

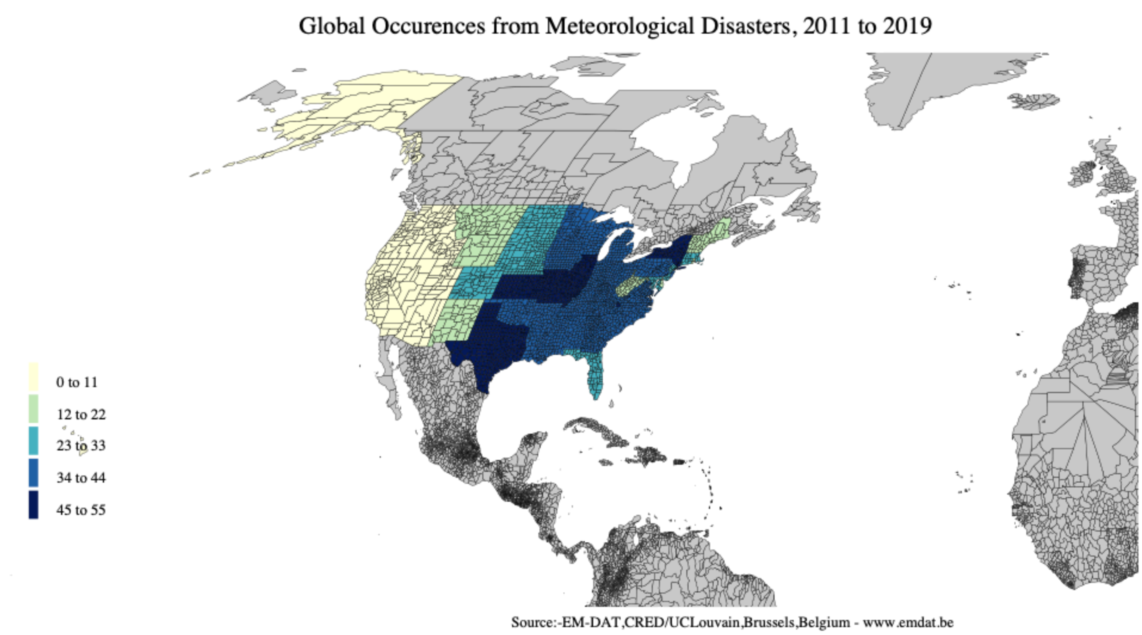

Figure A4. Total Number of Climatological Disaster Incidences in the US from 2011-2019

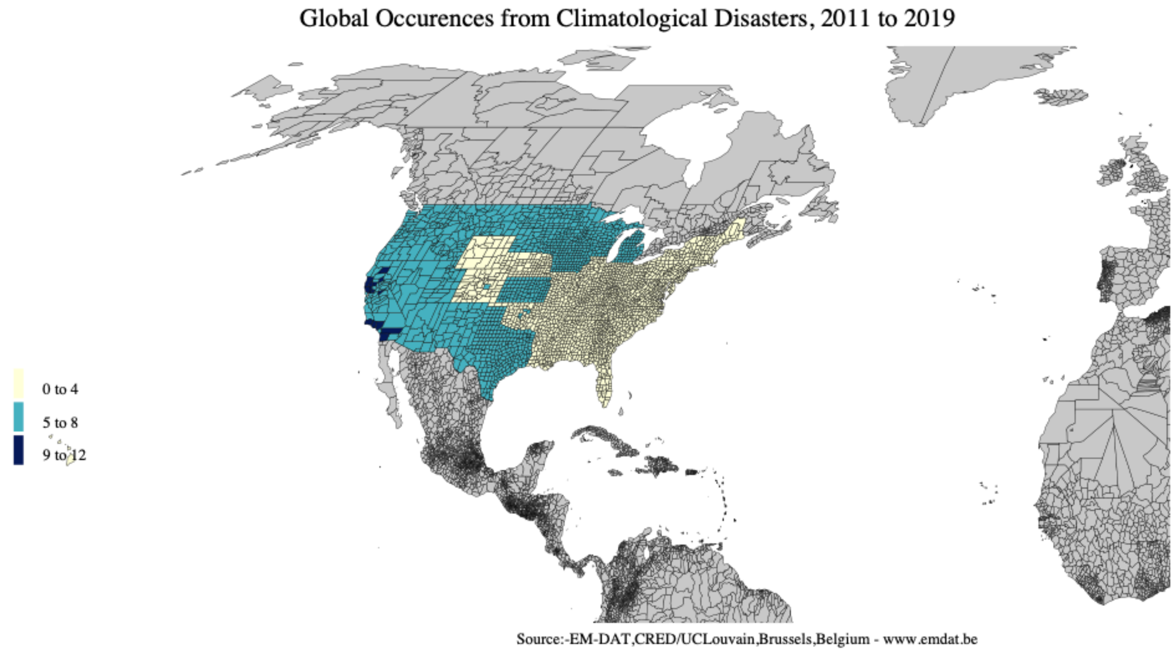

Figure A5. Total Number of Geophysical Disaster Incidences in the US from 2011-2019