After the Storm

Impacts of natural disasters in the United States at the state and county level

Danjie Fang

Professor Michelle P Connolly, Faculty Advisor

Professor Christopher D. Timmons, Faculty Advisor

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Abstract

Empirical research on the impact of natural disasters on economic growth has provided contradictory results and few studies have focused on the United States. In this thesis, I bridge the gap by examining the merits of existing claims on the relationship between natural disasters and growth at the states and county level in the U.S. I find that climatological and geophysical disasters have a small and negative impact on growth rates at the state level, but that this impact disappears over time. At the county level, I find that tornados have a slight but negative impact on per capita GDP levels and growth rates over a five year period across three states that experience this natural phenomenon. Controlling for FEMA aid, I find that there may be upward omitted variable bias in regressions that do not include the amount of aid as a variable. I find evidence that FEMA aid has a small but positive impact on growth and per capita GDP levels at both the county and state level.

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Introduction

Natural disasters are not new. Our understanding of the ancient world points to evidence of many encounters between civilizations and volcanic explosions, earthquakes, floods, and plagues. Though humans have fallen victim to such events for over millennia, they continue to perplex policy makers, as evidenced in recent years by recovery debacle of Hurricane Katrina. Even in the United States, policy makers are unsure as to how to appropriately respond to these events of natural calamity. They have also received very little guidance from academia, which has mostly taken a piecemeal approach to the issue from a wide variety of disciplines (Alexander, 2000).

I pause here for a moment to examine some definitions for natural disasters most frequently seen in contemporary literature. Natural disasters are derived from natural hazards, which are geophysical events characterized by a significant departure from climatic norms or trends e.g. floods would signify significant departures from average rainfall levels for an area. These hazards might be predictable and follow seasonal and geographic patterns, as in the case of hurricanes and typhoons, or they may be highly irregular in terms of their reoccurrence as in the case of floods and droughts. Natural hazards are distinct from technological hazards (explosions, releases of toxic materials, structural collapses etc.) and social hazards (e.g. terrorist attacks) in that they originate in the biosphere, lithosphere, hydrosphere or atmosphere (Alexander, 2000). Alexander defines a natural disaster as "some rapid, instantaneous or profound impact of the natural environment upon the socio-economic system."[1] Furthermore, he stresses that these impacts are concentrated as to distinguish them from common malaise across the world such as disease or childhood malnutrition.

[1] Alexander 2000 (p.4)

Empirical evidence on the causal relationship between natural disasters and growth for the U.S. is scarce. There are some case studies that suggest that disaster may have a positive impact on the economy. For example, a study of the Earthquake in Alaska in 1964 shows that government aid provided economic windfalls that benefitted the Alaskan by providing opportunities to upgrade and modernize public infrastructure and other capital (Kunreuther and Fiore, 1966). It is also argued that the 1994 Northridge earthquake helped transition the area from a dying aerospace industry, to newer fields of green manufacturing and bioscience that created opportunities for growth (International Economic Development Council, 2010). According to Rozario (2010), the fire of Boston 1676 created the space for better and safer infrastructure that was especially well-suited for the commercial expansion of the 19th century. He also credits the Great Chicago Fire of 1871 for transforming Chicago into the fastest growing city in the Western Hemisphere.

These examples suggest that infrastructural improvements and the adopt of better technologies in the wake of a disaster are the sources of improvements in the economy of the affected area. However, focusing on discrete events that lend themselves well to being a poster child for disaster recovery may paint an overly rosy picture of the impact of natural disasters. Alexander (2000) points out that "a rigorous approach to natural disasters requires that we look for the common regularities in each event"[2] and this may require understanding that may only be gleaned from a more broad based approach.

When approaches are attempted, however, they yield contradictory results, with some literature suggesting positive effects, and others suggesting negative or no effects on the economy in the long run. Taken together, the literature seems to only agree that disaster impacts vary depending on type of disaster, time frame, and location of the event. This provides very

[2] Alexander (2000) p.3

little guidance for policy makers on how they should structure their responses to best mitigate the effects of disasters, as what may be an appropriate action for one event does not necessarily translate to another. There is also an apparent tension in the scope of experiments in this field—how to be broad enough to capture Alexander's "common regularities" across disasters without being so broad as to lose the effect of the disaster in a sea of noise altogether.

In this paper, I will seek to bring clarity to some of these questions by focusing specifically on the United States. As some previous researchers have noted, disaster impacts on the economy are very much a function of its current state and types of institutions that govern it. Thus focusing on only one country would control for some factors that are unique to the country itself while maintaining enough variation across regions to be able to shed some useful light for policy makers. The homogeneity of states and counties relative to countries may reduce omitted variable bias. Looking across time in the U.S. may also give clues on how advancements in protection and forecasting technologies have altered the impact of disasters. There is also not very much regional research, and what does exist is mainly interested in developing countries, and such findings may not be applicable to U.S. My work will attempt to address these particular atrophies in the literature.

Conducting such an experiment in the U.S. is feasible because the country is fairly large and geographically and climatologically varied, experiencing several types of natural disasters every year. These disasters are also not a trivial matter. Chart 1 and Chart 2 show the top ten states in the U.S. in terms of damage sustained and number of people killed and affected for the thirty year period from 1970-2000. The states of California [$38.8 billion], Florida [$28 billion], and Texas [$18.3 billion] top the chart for damage in current dollars, while Florida [1 million], New York [0.71 million], and Pennsylvania [0.47 million] are at the top for persons killed and affected. During this period there were a total of 1,356 climatological, geophysical, hydrological, and meteorological[3] events according to EM-DAT[4]. Breakdowns of these events by disaster category can be found in Chart 3. In general, the most frequent type of disaster during this period is meteorological storms.

According to the Federal Emergency Management Agency (FEMA), there were 99 major disaster declarations made in 2011. Disaster declarations are made when the scope of the recovery in the aftermath of a disaster exceed the capabilities of the local government, so it can be expected that many more minor disasters occur in the U.S. that do not require FEMA attention. With a rising trend in both the level of disaster damage and frequency of disasters in the U.S. [Graph 1], it is important to identify the impact these disasters and FEMA aid have had on U.S. economies.

There is also some evidence these shocks have been increasing in frequency globally, with more major disasters predicted in the coming years. According to Huppert and Sparks, we live "in times of increasing vulnerability to extreme natural hazards."[5] Insurance company Munich Re recorded 960 natural hazards in 2010, the most notable of which are wildfires in Russia, devastating floods in Pakistan, and major earthquakes in Chile, China, New Zealand, Haiti, and Japan. Lying at the source of these disasters may be a combination of global climate change and vulnerabilities created by the people who inhabit these areas and the institutions that govern them. It is unclear, however, how much of this increase may be simply the result of

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[3] Climatological (extreme temperature, drought, and wildfire), geophysical (earthquake, volcano, and dry mass movement), meteorological (storm, tornado), and hydrological (flood, and wet mass movement) disasters all fall under the umbrella of natural disasters.

[4] EM-DAT is a database maintained by the Centre for Research on the Epidemiology of Disasters (CRED) which collects data from various sources including UN agencies, non-governmental agencies, research institutions, the press, and insurance companies. EM-DAT includes data on events from across the world from 1900-present day. For an event to be recorded in EM-DAT, it must meet one of the following criteria: 1) 10 or more people were killed 2) 100 or more people were affected 3) there was a declaration of state of emergency or 4) there was a call for international assistance.

[5] Huppert and Sparks (2006) p.1875

better measurement instruments and disaster reporting. Nonetheless, it is surprising that considering their frequency, dire impacts on the lives and well-being of so many people and the speed of development, there is relatively little literature on their effects on the economy, especially with regards to growth. My goal with this paper is to add the current discussion and bring it closer to understanding the full narrative of the natural disaster.

In this thesis, I examine the merits of previous claims concerning the impact of disasters on economic growth and output in the long run. I will also address the question of how disaster relief may have changed the impact of these disasters, and challenge some of the effects the current literature is describing.

Literature Review

The book *Economics of Natural Disasters: Implications for Federal Policy* by Dacy and Kunreuther (1969) is one of the first works of economic research on natural disasters. However, the earliest empirical work on the topic was not conducted until much later by Albala-Bertrand (1993). Comparing before and after data from 26 countries and 28 disasters, Albala-Bertrand finds that on average, GDP growth rates are higher in the year immediately following a natural disaster (by 0.4%; 0.7% higher if only third world countries are included). He finds that there is no impact on GDP levels and the impact on growth rates disappears after one to two years. These findings are contrary to the perceived view at the time that disasters have a negative effect on GDP in the short run (Albala-Bertrand, 1993). There are many limitations to this initial study, including the small sample size and its bias towards developing countries. Since then, researchers have appropriated more sophisticated tools and larger dataset in their empirical works, but there remains a lack of consensuses as to the appropriate approach and technique to this question, as well as the subsequent results.

The body of literature on the topic generally follows two directions of research. The first examines the short run impact of disasters and include Albala-Bertrand (1993), Kahn (2005), Raddatz (2007), Strobl (2008), Noy (2009), Rodriguez-Orregia et al. (2009), Leiter et al. (2009), Mechler (2009), and Hochrainer (2009). The second line of research examines the medium and long run impacts of disasters and include Skidmore and Toya (2002), Skidmore and Toya(2007), Noy and Nualsri (2007), Loayza et al. (2009), and Raddatz (2009).

Skidmore and Toya (2002) was the first major paper to look at the long run impacts of natural disasters. Their counterintuitive result has sparked much of the subsequent research.

Using a cross sectional regression, they find a positive relationship between the frequency of climatic disasters and average per capita GDP growth rates across 30 years.

Skidmore and Toya (2002) rely on a modified version of Schumpeterian "creative destruction" process to explain their findings. They suggest that the physical capital destroyed during a disaster is frequently replaced with more productive capital during reconstruction. Furthermore, disasters can reduce the expected return to physical capital, creating a substitution effect towards human capital, benefitting growth in the long run. These theories are supported with the finding that disaster frequency is positively correlated the average growth rate of a country's total factor productivity (TFP) and human capital accumulation (Skidmore and Toya, 2002). On the other hand, they find no effect of geologic disasters on GDP growth and suggest that the greater loss of life in these situations counteracts any positive effects disasters may have.

There are several drawbacks to their study, however, and subsequent research has been aimed at addressing these shortcomings. First, they use the cross-sectional average for GDP growth rates across 30 years from 1960-1990, so any correlations they find would describe a loose relationship at best. Moreover, by looking only at frequency, they lose a lot of important information regarding the intensity and timing of the disasters measured.

Noy and Nualsri (2007) attempt to improve upon some of the weaknesses of Skidmore and Toya (2002) in their study and acquire contrary results. By using the dollar amount of property damage and number of deaths instead of frequency, they are able to capture an additional measure of magnitude in their disaster variables. Using panel data with fixed-effects, they are also able to reduce time invariant omitted variables that may have affected Skidmore and Toya (2002) and produced spurious results. Using the same baseline as Skidmore and Toya (2002), they find that shocks to physical capital have no effect on growth, but shocks human capital have a significant, negative effect on the 5 year growth rates of Non-OECD countries. There no significant effects on the growth rates of OECD countries. This suggests the identities of countries included in a sample may have an impact on the results.

Loayza et al (2009) offer a further consideration when they argue that "different types of disasters can have diverse (even opposite) effects on growth"[6]. They propose the disaggregation of variables to single out effects that may be lost in aggregation. Focusing on medium-term economic growth in 5-year periods (in accordance with Noy and Nualsri (2007)), they observe the intensity (proportion of population affected) of storms, earthquakes, droughts, and floods on the growth of three different sectors (agriculture, manufacturing, and service). They find that droughts have a negative impact in both agriculture and manufacturing sectors, decreasing the overall GDP growth rate by and average of 0.6 percentage points per year, and moderate floods have a positive impact on both sectors (agriculture and manufacturing), increasing GDP growth rate by around 1 percentage point a year. They suggest that the benefit of floods (and detriment of droughts) may be derived from their impact on the water supply which affects agriculture and electricity generation (hydropower) and subsequently the agricultural and industrial sectors. There are no statistically significant results from storms and earthquakes. Finally, they find that all severe disasters have a strong negative effect on growth. They hypothesize this is because large disasters completely destroy the mechanisms (e.g. infrastructure) through which positive effects have traveled.

Beyond modifying the measures of variables, some researchers have moved to change the methodology of the research. Raddatz (2009) argues that previous studies have relied on some controversial identification assumptions, i.e. the predeterminedness of variables, and uses a different empirical approach from his predecessors. By applying a Vector auto-regression (VAR)

[6] Loayza et al. (2009) p.3

model, Raddatz estimates the per capita GDP levels of countries in the years after a natural disaster. He finds that a single climatic disaster has a moderate impact on output, reducing real per-capita GDP by 0.6% by the 10th year after the event, with 0.5 of the 0.6% reduction occurring in the first year after the disaster. Geological disasters have no statistically significant impact on per-capital GDP and all other disasters create a 2% decrease in per capita GDP.

Along a similar vein, Cavallo et al. (2010) use a comparative event study approach, constructing counterfactuals of a country's GDP level across time with a synthetic control group and comparing it with the observed GDP trajectory. They also refine their research to individual buckets of medium, large, and very large disasters. Using empirical growth rates of similar countries that did not experience the catastrophic disaster (for up to 10 years past the disaster date), they construct mathematical estimates for the path the country's GDP should have taken, had it not experienced the event. They argue that this empirical method is a better alternative to using longitudinal data with fixed effects, because it allows some degree of control over country specific characteristics and allows these characteristics to vary across time. While analyzing the merits of such an approach is beyond the scope of this paper, their findings are consistent with those of Raddaz (2009). They findd a negative impact of disasters on GDP levels, but only for the largest disasters. Specifically, real GDP per capita is almost 10% lower than its initial level 10 years after a disaster (the GDP of its synthetic control countries had risen 18%, suggesting a cumulative loss of 28%). However, for disasters that didn't fall into the category of the largest of the large, they found no significant impact on GDP levels. When they controlled for cases where disasters triggered radical political revolution, they found that there were no effects at all even among the largest of the large disasters. However, their sample of disasters is heavily biased towards third world countries which may also explain their findings.

Finally, though most of the literature on natural disasters and economic growth is concerned with impacts at the country level, a couple of studies look at smaller economic areas, notably Rodriguez-Oreggia (2008) who observed Mexican municipalities and Strobl (2008) who looked at U.S. counties. Both observed negative impacts in the short run. To my knowledge there is no research that looks at long or medium run impacts at the regional level.

In summary, research on the impacts of natural disasters has generally provided contradictory results. This paper will supplement current research by examining more closely disaster impacts in the U.S. In particular, I will observe disasters at both the state and county level from the years 1970-2010. Furthermore, I will include the level of FEMA obligations as a variable to explore the question of whether or not the absence of aid from previous studies may have biased findings in the past.

Theory

Because much of the existing literature focuses on the impacts of different types of events (e.g. large disasters versus small, climatic versus geologic, disasters in OECD countries versus non OECD), it suggests that there are many channels through which disasters may affect GDP growth and output in the long run. Here, I will suggest three situations that lead to three very different outcomes

First, I assume that there is an initial negative shock to GDP after a disaster, due to the immediate decrease in the original capital stock and the partial/full shut down of the economy. After this initial shock, an area may grow at a faster or slower rate, or at the same rate. If an area experiences these negative shocks to GDP very frequently, what we may observe in the long run is no change in GDP or a negative change in GDP because the country has not had a chance to capitalize on any positive effects (if there are any) of rebuilding before the next disaster.

In a second case, there may be adoption of the newest technologies during the reconstruction period that increases the productivity of the capital stock. Prior to the disaster, these improvements may have been delayed because of decisions of companies to hold off making new investments due to particular constraints. This could cause some regions to grow faster for a period after a disaster. This type of productivity growth, however, is limited by the existing technological frontier of the country.

Finally, the disaster may result in the adoption of government policy that expands the technological frontier of the country by increasing investments in research and development. This may produce larger more sustained impacts on regional growth rates.

To better explain these situations, I begin with the classic production function with human and physical capital:

$$Y = AK^{\alpha}(hL)^{1-\alpha} \quad [1]$$

where Y = output; A = measure of productivity; K = quantity of physical capital; L = number of workers; h = quantity of human capital per worker. Dividing by L will put everything into per worker terms, and I am left with:

$$y = Ak^{\alpha}h^{1-\alpha} \quad [2]$$

Taking the natural log of both sides of equation [2] and differentiating with respect to time, I obtain the Solow growth model:

$$\hat{A} = \hat{y} - \alpha\hat{k} - (1-\alpha)\hat{h} \quad [3]$$

In the first case, where natural disasters present a negative shock to the economy, we expect to see an immediate fall in the capital stock leading to a fall in output in the short run. However, if these shocks become very frequent, it could potentially lower the investment in k, leading to a lower growth rate and levels of output in the future.

The second case describes one in which the reconstruction after a natural disaster will improve the productivity of capital. Most endogenous growth models use investment in research and development to explain gains in real GPD per capita growth rates in the long run. I choose to focus on endogenous technological change because it is a likely venue through which natural disasters may impact long run economic growth. Since growth is driven by two main forces, factor accumulation and productivity, and there is a finite limit to the amount of capital that can be accumulated, the key component for sustained, long run economic growth is productivity. But why would the replacement of damaged capital stock result in greater productivity?

I base my hypothesis on the idea that not all R&D leads to products that are easily put onto the market for use immediately. For example, though the knowledge might exist on how to engineer better and build safer cities, it is very hard to knock down existing infrastructure and convince people that it is good for them (the classic "if it ain't broke why fix it?" conundrum). Literature on embodied technical change seems to suggest the possible positive effects of shortening the average life of capital (Hulton, 1992). Hulton finds that best practice technology in manufacturing is 23% more efficient than the average technology of its day. At the same time, he also finds empirically that a 1 percentage point increase in the growth rate capital formation only induces a small 0.127 percentage point increase in real output growth, with a direct effect of 0.103 percentage points and an indirect embodiment effect of only 0.024 percentage points. This seems to suggest that the speed of capital formation alone is not enough to have a significant impact on output. However, the reconstruction that occurs after a disaster event may be of a very different nature than the average investment patterns for manufacturing plants. Natural disasters have the power to justify the need for new capital investment in those areas that firms would not normally consider investing in, e.g. infrastructure changes.

There are economic models describing this irregular investment pattern in firms, incorporating the idea that firms are not able to invest in the newest technology immediately. This is based on the assumption that capital investment has some inherent rigidities. There is evidence of this behavior in real life. Doms and Dunne (1993) looked at investment patterns in 12,000 plants in US manufacturing over the 17 year period from 1972-89. They construct a series on the proportion of the total equipment investment of the establishment made in each year. They find that on average, the largest investment episode accounted for more than 25% of the 17 year investment of an establishment, and was often followed by a second large investment spike that combine to form on average almost 40% of the total investment of the average firm. This concept is known as microeconomic lumpiness, and it is expected that this lumpiness will disappear once data for all of the firms are aggregated. Caballero (1997) argues, however, that aggregated microeconomic lumpiness shows up on macroeconomic data as well. Relying on his model which incorporates rigidities with respect to investment, I suggest that the frequent occurrence of natural disasters can reduce the amount of time between adjustments.

Caballero defines a measure of capital "imbalance" for each individual firm as:

$$Z \equiv \frac{K}{K^*} \qquad [4]$$

Where K is the level of the firm's capital stock and K* is the desired level of capital stock. To model the infrequency of investment actions, the cost of adjusting the stock of capital must increase sharply around the point of no adjustment, which Caballero defines as C. Furthermore, the size of this cost is expected to be proportional to the size of the adjustment, but to keep the equation simple, it has been excluded from the aggregate model. Under these conditions, Caballero then defines the variable x as a capital imbalance index centered around zero. This index is a logarithmic function of the ratio between the capital imbalance and the cost of investment, equation 5.

$$x \equiv \ln(\frac{Z}{c}) \qquad [5]$$

Here, the probability of adjustment rises with the absolute value of x. Letting Λ(x) symbolize the function describing the probability of adjustment given x, the expected investment made by the individual firm can then be modeled in equation 6:

$$E[I_{it}/K_{it}|\, x] = (e^{-x} - 1)\Lambda(x) \approx -x\Lambda(x) \qquad [6]$$

The aggregate is then defined as the behavior of the average, and the average investment rate for all firms with an imbalance index of x then becomes:

$$\left(\frac{I_t}{K_t}\right)^x = -x\Lambda(x) \tag{7}$$

Averaging across all capital imbalance indexes x at time t becomes:

$$\left(\frac{I_t}{K_t}\right)^A = -\int x\Lambda(x)f(x,t)dx \tag{8}$$

Where $f(x,t)$ is the cross sectional density of establishment's capital imbalances before investment takes place.

I propose that natural disasters increase the capital imbalance, Z, increasing x and increasing the probability of adjustment, described by Λ(x). Since the natural disasters I choose will be large enough to impact more than just one firm, averaging across all x should increase the investment to capital ratio $\left(\frac{I_t}{K_t}\right)^A$.

If it is the case that natural disasters speed up capital investment, and the type of capital invested in after a natural disaster incorporates technologies that improve productivity for the economy, then there is an improvement in the technology scalar of the production function (A), leading to an increase in Y. This also leads to an increase in the growth rate of A, resulting in an increase in the growth rate of output in the long run.

The idea may not be as farfetched as it may seem, because there is evidence of such behavior in other events of economic shock. Caballero (1997) points to the fact that obsolescence and scrapping are driven by both slowly moving technological trends and sudden changes in the economic environment. In particular he cites the impact of oil shocks on the scrapping of old and fuel-inefficient planes documented by Goolsbee (1995).

It is important to note, however, that this improvement is limited by the technological frontier of the country. The improvement in technology observed in this case would be one of copying and installing existing technology, and not of inventing new technology on their own. Since this is also a viable possibility, it will be observed exclusively in the third case. For now, I will rely on a model of technological transfer to explain an increase in long run growth rates at the state and county level. I will refer to the two country model for technological imitation as described by Weil (2005).

Consider two economies where economy 1 is technology leader and economy 2 is the technology follower and the economy of interest with respect to the impact of natural disasters. Prior to the event, the technology follower is at a lower level of technology and constrained by rigidities in capital investment. However, the natural disaster breaks the rigidities and allows the technology follower to "copy" or implement the latest technology available, moving it to the same level of technology as the technology leader.

According to Weil's model, the growth rate of technology in country 1is:

$$\widehat{A_1} = \frac{\gamma_{A,1}}{\mu_i} L \qquad [9]$$

Where $\gamma_{A,1}$ is the fraction of workers in economy 1 doing R&D, A_1 is its level of technology, and μ_i is its cost of invention, and L is the size of the labor force.

Assuming that the labor forces of the two countries are the same, the growth rate of technology in country 2 is then defined as:

$$\widehat{A_2} = \frac{\gamma_{A,2}}{\mu_c} L \qquad [10]$$

Where $\gamma_{A,2}$ is the fraction doing R&D in economy 2, A_{is} its level of technology and μ_c is its cost of copying the technology from economy 1, equal to some function that describes the relationship between the ratio of technologies.

$$\mu_c = c(A_1/A_2) \qquad [11]$$

The growth rate of technology in economy 2 is then seen as growing towards a steady state, where we expect to see a convergence to some ratio of A_1/A_2 where two economies will grow at the same rate. At this point, we expect that:

$$\widehat{A_1} = \frac{\gamma_{A,1}}{\mu_i} L = \widehat{A_2} = \frac{\gamma_{A,2}}{\mu_c} L \qquad [12]$$

Here, I predict that μ_c is increased by some rigidities inherent in capital investment, and that natural disasters reduce these rigidities and thus the cost of copying. By lowering μ_c, we then expect to see an increase in the growth rate of technology in economy 2 towards the steady state. Since the growth rate of technology increases, we will then predict an increase in the growth rate of output in the long run.

However, it may well be that the reconstruction that occurs after a natural disaster is just to replace capital with the same capital that was destroyed, because producers have strong incentives to replace damaged capital with the same capital in order to rebuild more quickly. It could also divert important resources away from research and development in the rebuilding process. In their work, Hallegatte and Dumas (2007) examine embodied technical change in the context of reconstruction after natural disasters using a modified Solow growth model with price and wage rigidities. Through their purely theoretical framework, they find that strong negative shocks like natural disasters have no real impact on long run economic growth, even under the strongest assumptions of full incorporation of the most recent capital during reconstruction. They admit to some limitations of their model including their assumption that the productivity of most recent capital grows at a constant rate. This cannot take into account production of technological change through education, learning and doing, and research and development. However, if this is the case, then the capital after reconstruction will have the same productivity and we will expect no effect or a negative effect on the long run growth rate, after incorporating the negative shock to the economy and resource diversion away from R&D. In sum, the theoretical impact of natural disasters on the productivity of capital in investments during reconstruction is ambiguous.

Finally, policies instituted in the wake of a natural disaster may alter the rate of innovation. Here, they may alter the growth in A, which is a function of research and development, human capital, and A of the previous period. Policies may encourage or discourage investments in R&D. If the disaster even leads to a decrease in R&D from the private and/or public sector, we will see a fall in the change of A. Furthermore, if the natural disaster results in a declination to adopt new technologies, we may also see the change in A fall, which may have a negative effect on the growth rate of output.

Natural disasters may have a negative impact on R&D because some natural events can also trigger a chemical disaster like the damages incurred by the Japanese Nuclear power plants after the Earthquake and Tsunami of 2011. This may evoke a fear effect that will stymie investment in nuclear power plants and new R&D in that industry. For example, no new nuclear power plants have been built in the US since the Three Mile Island accident in 1979.

Because the benefits of improvements in environmental technologies accrue mostly to the public and are a social good, there is usually little incentive for the private sector to invest in them. Thus environmental technology R&D is mostly funded by the government and other public funds (Popp et al. 2009). Subsequently, public opinion has great sway over policy and regulation of these industries in the US, and when a natural disaster results in bad press about these technologies, further developments in productivity in these industries may be hindered through the irrational fears of the public in the aftermath of a disaster.

However, these events may also increase interest in investing in safer, better technology (e.g. forecasting instruments etc.) or in R&D, in which case we might expect to see a positive change in A leading to a positive impact on the growth rate of output. As in the second case, the impact of a natural disaster here is also ambiguous.

In all, I have delineated three channels of impact on the economy from a natural disaster, the last two of which have, theoretically, ambiguous impacts on long run GDP growth rates. Thus, depending on which effects dominate, it is possible to have a positive, negative, or no relationship between disasters and the regional economy in the long run. Furthermore, the impacts may differ by type of natural disaster, size, or region of observation, or a combination of all three.

Data

Following other studies on long-run growth, I use panel data where observations are made over time for each geographic area. The data include observations from 50 States in the U.S. from the years 1970-2000. Data on natural disasters were obtained from the EM-DAT database maintained by the Centre for Research on the Epidemiology of Disasters (CRED). The data are collected from various sources including UN agencies, non-governmental agencies, research institutions, the press, and insurance companies. EM-DAT includes data on events from across the world from 1900 to present day. For an event to be recorded in EM-DAT[7], it must meet one of the following criteria: 1) 10 or more people were killed 2) 100 or more people were affected 3) there was a declaration of state of emergency or 4) there was a call for international assistance. EM-DAT includes basic information on the location, start and end date, and name of disaster (if applicable). Furthermore, EM-DAT includes estimated damages and number of people killed and number of people affected for each event. EM-DAT collects information at the level of the event, so for the purposes of my analysis, it was necessary to create estimates of damages and number of people killed and affected at the state level.

Economic losses for events that occurred in more than one state are weighted by each state's relative GDP to create an estimate of each state's share of the total damage. The resulting estimates for are divided by the state population to create a per capita value, and summed by disaster subtype over a period of five years to create the economic loss variables used in the regression as shown in equation 13:

[7] Loayza et al. (2009) has pointed to some downfalls of using EM-DAT on estimated damages including lack of a standard procedure and missing data. However, economic damages are an important measure of the magnitude of a disaster, especially in the U.S. where we do not expect the level of human death toll that can arise from disasters in developing countries, and may provide channels through which improvements in productivity can arise.

$$HIT_{i,t} = \sum_{j} \frac{Estimated\ Damages_{i,t,j}}{Population_{i,t}} \qquad [13]$$

Where *j* indexes the number of events that took place within the five year period *t*, and *i* is the state the event took place. This allows the HIT variable to capture the impact of both the magnitude and frequency of a natural disaster.

The variable measuring human loss is similarly created. Total impacts on the population for each event are weighted by the relative size of the state's population for all states involved. Population impacts are measured as the sum of the number of people killed and affected[8]. This value is divided by the population size of the state at that time and summed by disaster subtype over the period of five years according to equation 14:

$$AFF_{i,t} = \sum_{j} \frac{Total\ killed\ and\ affected_{i,t,j}}{Total\ population_{i,t}} \qquad [14]$$

EM-DAT categorizes events by subtype, four of which I have included in my regressions. They are climatological (extreme temperature, drought, and wildfire), geophysical (earthquake, volcano, and dry mass movement), meteorological (storm, tornado), and hydrological (flood, and wet mass movement). A more detailed description can be found in Appendix Table D. Graph 4 and Graph 5 present breakdowns of disaster damage by these subtypes. Generally, Meteorological disasters are the greatest source of economic damage and persons killed and affected by natural disasters in the U.S. in this time period.

The dependent variable is per capita GDP and per capita GDP growth rates over 5 years. The data are observed from the period 1970-2000 and are obtained from the Bureau of Economic Analysis (BEA). State level capital stock is included as an explanatory variable and data is

[8] According to EM-DAT, the category "killed" includes persons confirmed as dead and persons missing and presumed dead. The category "affected" includes people requiring immediate assistance and displaced or evacuated people.

obtained from Yamarik (2011). A measure of human capital stock is also included as an explanatory variable and obtained from the U.S. Census Bureau. I measure human capital by the percentage of the population 25 years or older with a bachelor's degree or higher. Summary statistics can be found in Appendix Table A and Appendix Table C.

Data on total obligations from the Federal Emergency Management Agency (FEMA) at the state level are provided by Thomas Garrett from the paper Garrett and Sobel (2002). Summary statistics are provided in Appendix Table A and C. The data are obtained for the years 1989-1999. Graph 9 presents the average real per capita FEMA obligations for this decade. The general trend across time is upward.

When examining disaster impacts at the county level, I obtain tornado, hail and wind damage data from Severe Weather Database maintained by National Oceanic and Atmospheric Administration. This database is accessible online at http://www.spc.noaa.gov. Like the EM-DAT database, the Severe Weather Database collects data by event, so damage for events that occurred in more than one county were weighted by that county's GDP as a fraction of the total GDP of the all the counties involved. As I've done before, the total damage is summed up for each county by year and divided by the size of the county's population. This changes the value to per capita terms. The resulting estimate is summed up over the period of five years to create disaster variables for tornado and hail and wind damage. I observe all 257 counties from Arkansas, Kansas, and Oklahoma. The data are collected for the years 1999-2009.

The dependent variables for the county level regressions are measures of the per capita GDP and per capita GDP growth rates over five years. The observations are made for the years 1999-2009 and are obtained from the BEA. Capital stock measures for this period are included as explanatory variables and are calculated by the perpetual inventory method according to the equation:

$$\dot{K}_{1999} = \frac{I_{1999}}{g + \delta} \quad [15]$$

Where g is the average annual growth rate of real capital investment by manufacturing establishments, δ is a depreciation rate of 5% chosen as the average of statewide depreciation from Yamarik's (2011) state level estimates. The initial level of capital for K in 1950 is also estimated from the Yamarik's (2011) state level figures. The level of capital for each county is calculated by their output relative to the state output. Manufacturing investment data for the period from 1999-2009 are obtained from the U.S. Census Economic Survey which is collected for the years 1997, 2002, and 2007. A proxy for human capital for this period is also included as an explanatory variable and is measured as the proportion of the population 25 years and older with a bachelor's degree or higher. Inter-period estimates are interpolated where measured data are not available. Summary estimates are presented in Appendix Table B and C.

FEMA data for the Public Assistance program is obtained from the data.gov for the years 1999-2009. The Public Aid assistance program provides aid for projects for public areas such as schools and roads and non-profits in the aftermath of a disaster (e.g. repair, debris removal and hazard mitigation). There is a separate FEMA program that provides aid to individuals and private businesses, but I was not able to obtain these data on the county level. On average, public assistance comprised around 53.2 percent of the total aid disbursed for the previous decade (1989-1999) according to Garrett and Sobel's (2002) state level data. All dollar values are real 2005 dollar values.

Methodology

I use a fixed effects model for both state and county regressions because it removes the effects of time invariant characteristics of each geographic area. I start with the following regression found in most growth literature.

$$y_{i,t} = \alpha_i + \beta y_{i,t-1} + \varphi X_{i,t} + \varepsilon_{i,t} \qquad [16]$$

Where $y_{i,t}$ is the real GDP per capita growth rate across the five year period and $X_{i,t}$ are the control variables included in the regression.

I include variables measuring the magnitude and frequency of natural disasters by time period and state as described in the previous section. I also control for per capita FEMA aid over the five years where data is available. This leaves me with the following four possible equations.

$$y_{i,t} = \alpha_i + \beta y_{i,t-1} + HIT_{i,t} + \varphi X_{i,t} + \varepsilon_{i,t} \qquad [17]$$

$$y_{i,t} = \alpha_i + \beta y_{i,t-1} + HIT_{i,t} + FEMA_{i,t} + \varphi X_{i,t} + \varepsilon_{i,t} \qquad [18]$$

$$y_{i,t} = \alpha_i + \beta y_{i,t-1} + AFF_{i,t} + \varphi X_{i,t} + \varepsilon_{i,t} \qquad [19]$$

$$y_{i,t} = \alpha_i + \beta y_{i,t-1} + AFF_{i,t} + FEMA_{i,t} + \varphi X_{i,t} + \varepsilon_{i,t} \qquad [20]$$

$HIT_{i,t}$ and $AFF_{i,t}$ are the magnitudes of economic and human damages as calculated by equation 13 and equation 14 for each sub-type of disaster: climatic, geologic, hydrological, and meteorological. $FEMA_{i,t}$ is the level of per capita FEMA obligations over the five year period t.

I follow a similar methodology for the county regressions, replacing the $HIT_{i,t}$ and $AFF_{i,t}$ variables with per capita tornado damage $TOR_{i,t}$ and hail and wind damage $HW_{i,t}$ over the five year period. This results in the following equations where $FEMA_{i,t}$ is included as the level of per capita FEMA Public Aid over the five year period.

$$y_{i,t} = \alpha_i + \beta y_{i,t-1} + TOR_{i,t} + HW_{i,t} + \varphi X_{i,t} + \varepsilon_{i,t} \quad [21]$$

$$y_{i,t} = \alpha_i + \beta y_{i,t-1} + TOR_{i,t} + HW_{i,t} + FEMA_{i,t} + \varphi X_{i,t} + \varepsilon_{i,t} \quad [22]$$

I weight the observations of each county by that county's average population, under the assumption that the behavior of more populous counties are likely to be more representative of the whole.

Results

Table 1 presents the results for the fixed effects level regression. The dependent variable is real per capita GDP for the state and the relevant time period for the regression are the years from 1970 to 2000. The magnitude of economic loss is measured as the real dollar value over the size of the state population. Total economic loss is broken down into climatological, geophysical, hydrological, and meteorological subgroups. All variables are in natural logs. The coefficients on both the physical and human capital explanatory variables have the expected sign and are statistically significant. To address any issues of endogeneity, a panel instrumental variable regression is run using lagged variables for human and physical capital. The results are very similar. The main difference is a slightly higher coefficient for human capital [0.0265] and lower coefficient for physical capital [0.501] and a higher R^2 (0.928).

None of the variables that measure economic losses from disasters are statistically significant. This is contrary to Raddaz (2009) who finds that a single climatic disaster decreases GDP per capita on average by 0.6 percent. Raddaz defines climatic disasters as climatological, hydrological, and meteorological disasters combined. Consistent with Raddaz, I find that geological disasters have no impact on GDP per capita. Two reasons for these contradictory results may have already been suggested by existing literature. First, there is evidence that disasters have significantly less economic impact on middle and high income countries Raddaz(2009). This is because a country’s level of development can impact its response to a disaster. According to Kellenberg and Mobarak (2011), “only when levels of development have reached a certain point can nations successfully address weak institutions, create better insurance markets, require more stringent building standards, reduce corruption, and instate more advanced warning and emergency response systems."[9] Cavallo (2010) also finds that there is only a significant impact of natural disasters on GDP levels in cases of catastrophic disasters. Perhaps the disasters in my dataset are simply not large enough to affect a lasting impact on a state economy.

Columns (5) through (6) run the same regressions while attempting to control for the effects of FEMA through a FEMA dummy variable which represents the years when FEMA is in existence (1979). Consideration of disaster aid is something that not many empirical works in the field have attempted. An exception is Yang (2008) who looks specifically at financial flows, including official development assistance (ODA) in the aftermath of hurricanes. He finds that when ODA was granted, (usually to poorer countries) it was enough to replace almost 80% of the damage. In my regressions, the dummy variable is negative and statistically significant, but cannot be interpreted as a FEMA effect because it also captures many other time specific effects.

Table 2 presents the fixed effects level regression run for the same years and states as Table 1. The measure in these regressions for disaster loss is the proportion of people in the population who are killed and affected (affected is defined as the people requiring immediate assistance during the emergency, including displaced or evacuated people). Again, the coefficients on the capital stock and human capital variables have the expected sign and are statistically significant. Again, my coefficients for my disaster variables are not statistically significant and inclusion of the FEMA dummy variable (columns 5 through 8) is negative and statistically significant, but cannot be interpreted.

[9] Kellenberg and Mobarak (2011) p.304

From my regressions, it appears that disasters in the U.S. do not have a significant impact on output levels of the states. This holds whether we consider disasters through their human capital shock, physical capital shock, or by subcategory.

In Table 3, I turn to the question of the impact of disasters on economic growth rates. Table 3 presents results for my growth regressions for all states at five year periods from the years 1970 to 2000 according to equation 17. The dependent variable is the per capita GDP growth rate over five years and the disaster variables are the same as those presented in Table 1. Year dummies were included to control for the presence of FEMA. For brevity, their coefficient estimates are not included. All disaster variables are in natural logs. The coefficients for the growth of capital stock and human capital have the expected sign and are statistically significant. The coefficients for the variables measuring economic loss for climatological (extreme temperatures, droughts, wildfires) and geophysical disasters (earthquake, volcano) are negative and statistically significant, though small. They are [-0.000741] and [-0.000715] for climatological and geophysical disasters respectively. The median amount of climatological and geophysical disaster damage over five years would decrease the average GDP growth rate by 0.00245 and 0.00269 percentage points respectively over that same period. Hydrological and meteorological disasters appear to have no effect on statewide output growth rates. At first glance, this result may be concurrent with Loayza et al. (2009) who find that droughts have the most negative, statistically significant impact on growth rates (0.6 percentage points a year) at the country level. However, as Graph 3 show and Chart 3 show, droughts only comprise 12.8 percent of climatological disasters in my dataset, so it is unclear whether the impact comes through droughts, wildfires, or extreme temperature. Further analysis would be needed. Loayza et al. (2009) also have findings of no significance on earthquakes and a positive impact of floods on growth rates. The only concurrence is that meteorological disasters (storms in Loayza et al.) do not have a significant impact on growth.

My finding that geophysical disasters have a negative impact on growth rates is contrary to most existing literature which finds no statistically significant effect, though some (Skidmore and Toya, 2002) have found a negative coefficient. This may suggest that the impacts of geophysical disasters are more localized and have more of an impact on a smaller region than for the entire country.

Table 4 presents the results for equation 19 with the variables that measure human losses. The coefficients for the growth of human and physical capital stock are statistically significant and consistent with Table 3. I find a negative and statistically significant coefficient [-1.267] for climatological disasters. For the median amount of disaster damage in terms of human loss over five years, there would be a 0.000016 drop in the average growth rate for the state. This is much smaller effect than the one for the impact of climatological disasters measured by economic loss in Table 3. The coefficient for geophysical disasters is not statistically significant and the coefficients for hydrological and meteorological variables are also insignificant. At least for the U.S., there seems to be a greater, negative impact on the growth rates through economic loss than through human impacts at the state level, though the elasticity for the human loss variable is much higher.

In summary, Table 1 through Table 8 show that climatological and geophysical disasters have a negative effect on the growth rates of states from 1970-2000. For climatological disasters, elasticity of the human loss variable is much higher. However, given the median amount of loss, economic damage seems to have a much greater effect. For geological disasters, damage to the human variable has no effect on growth rates, though economic damage has a small negative effect. No significant effects on growth were found for hydrological and meteorological disasters at the state level, and no effects were found for any type of disaster on the level of output of the state.

Inclusion of the level of FEMA obligations

As I mention before, it is not likely that inclusion of a dummy variable for the years that FEMA existed as an organization can adequately capture the effect of aid in my regressions. Table 5 presents the results for the level regressions that include variables that measure total per capita FEMA obligations at the state level for each subtype of disaster. Because I was only able to obtain total FEMA obligation data at the state level for the years 1989 to 1999, I run my regression for all states during this time period. All variables are in natural logs. The coefficients for human and physical capital stock are of the expected sign and statistically significant. Instrument physical and human capital stock with lagged variables produces very similar results. The coefficient for per capita physical capital is slightly higher [0.419], the coefficient for human capital is slightly lower [0.110] and the R^2 value is slightly lower [0.951]. In columns (1) through (4), I run the same regression as in Table 1 for the new time period 1989-1999.

Again, I find no statistically significant impacts on the state level of output for any variables that measure economic loss. In columns (5) through (8) I control for the level of total per capita FEMA obligation for the disaster subtype. I find a negative, statistically significant coefficient [-0.0310] for the geophysical economic loss variable and a positive, statistically significant coefficient [0.0402] for the geophysical FEMA obligation variable. This suggests that measuring disaster impacts without controlling for the level of aid provided in the aftermath can lead to upward bias of the estimates. Specifically, a 10 percent increase in the per capita economic loss from geological disasters over five years would have led to a 0.3 percent decrease in the state's per capita level of output, all else equal. A 10 percent increase in the per capita FEMA aid over five years for geological disasters would have led to about a 0.4 percent increase in the state's per capita output, all else equal. It is interesting that this negative effect of disasters and positive effect of aid on output is only observed for geophysical disasters. As shown in Graph 6 and Graph 7, the breakdown of FEMA aid by disaster subtype follows pretty well the breakdown of total economic damage during this period. This supports again the idea that the type of disaster matters in making claims for the effects on the economy of both the economic loss and governmental aid in a disaster situation.[10]

In columns (1) through (4) of Table 6, I present the results for the equation 18, run for the years 1989-1999. The dependent variable is the five year per capita GDP growth rate. All disaster variables are in natural logs and I use rolling 5 year windows. The coefficients for the growth of physical capital and human capital are of the expected sign and statistically significant. The small, negative effect on state growth rates from climatological and geophysical disasters found in Table 3 are not present in this new time period. It may be that states are better equipped to mitigate the negative effects of disasters on their growth in these later years, whether through experience and/or development. Likewise, there are no statistically significant coefficients for

[10] The regressions from Table 5 are run with the variables that measure human loss, but produce no statistically significant coefficients for the disaster and aid variables. This may be because FEMA aid more closely follows a measure of economic loss than a measure of proportion of population killed and affected (Graph 6, Graph 7, and Graph 8). These results are not included for brevity.

disaster and aid measures, when FEMA obligations are controlled for in columns (5) through (8).[11]

Smaller Economic Areas

From my results, I find that excluding variables for aid may result in upward omitted variable bias in disaster regressions and that natural disasters do not seem to have as much of an impact on state GDP in more recent years. This may be because states have become more adept at handling disasters and stemming their negative impacts on the economy as a whole. The question remains if this still holds when we move into even smaller geographic areas. According to Raddatz (2009), "it is often claimed that small states have a harder time dealing with natural disasters because of their inability to diversify geographically"[12]. Thus, we may see a larger impact of disasters on output at the county level than at the state level, and we may be able to observe impacts that may be subsumed at the state level.

Table 7 presents results for the fixed effects regressions at the county level. The dependent variable is the per capita GDP of 257 counties from Arkansas, Kansas, and Oklahoma and the period of observation is from 1999-2009. I look specifically at per capita tornado damage and per capita hail and wind damage. These are all considered types of storm damage and would be included under meteorological damage, for which I found no statistically significant effects on the economy at the state level. Finally, I control for per capita amount of FEMA aid provided through the FEMA Public Assistance program[13] for these damages to help

[11] I run the same regressions for the proportion of population killed and affected in Table 6 and there are no significant effects to report. The results were not included for brevity.

[12] P.12

[13] The Public Aid assistance program provides aid for projects for public areas such as schools and roads and non-profits in the aftermath of a disaster (e.g. repair, debris removal and hazard mitigation). There is a separate FEMA program that provides aid to individuals and private businesses, but I was not able to obtain data on the county level for the amount of aid disbursed through this program.

address some omitted variable bias. All variables are in natural logs. The coefficients of the physical capital stock and human capital stock variables are of the expected sign and are statistically significant. In column (1) where aid is excluded, the coefficient on tornado damage is negative and statistically significant, suggesting that tornados have a negative impact on the level of county irrespective of any positive effects that may come from aid. When FEMA public aid is controlled for the coefficient for per capita tornado damage is even more negative [-0.0290], implying that 10 percent increase in per capita economic loss from tornados over five years would have led to around a 0.29 percent drop in the level of per capita output in the county, all else equal. The coefficient for the FEMA aid variable is [0.00877] implying that a 10 percent increase in per capita aid over five years would have led to a 0.088 percent increase in the level of output, all else equal. The coefficient for the per capita hail and wind damage is not statistically significant, even when FEMA public aid is controlled for. The damage from hail and wind may not be severe enough to have lasting impacts at the county or the coefficient may still suffer from upward omitted variable bias because FEMA private aid is not accounted for in this regression.

Table 8 presents the fixed effects growth regressions at the county level following equations 21 and 22. The dependent variable is the five year per capita GDP growth rate. All disaster variables are in natural logs and I use rolling 5 year windows. The coefficients for the growth of physical capital and human capital are of the expected sign and statistically significant. The coefficient for tornado damage per capita is negative and statistically significant, even when FEMA aid is not controlled for, suggesting that tornado damage has a negative impact on county level growth rates. When FEMA public aid is controlled for, the coefficient on the tornado variable is even more negative [-0.00347]. For the median amount tornado damage over five years this implies a 0.000137 percentage point drop in average five year growth rates, all else equal. The coefficient for public FEMA aid is [0.000455]. For the median amount of FEMA public aid over five years (when granted) this suggests a 0.00022 percentage point increase in average five year growth rates. The coefficient for per capita hail and wind damage is statistically insignificant. It is unclear whether there is no lasting effect or if the coefficient still suffers from upward bias due to the omission of a measure of FEMA private aid.

The results show that disasters can still have a negative impact (albeit very small) on the economy at the county level across five year periods, even in the most recent years for the U.S. This effect may only hold or be most pronounced for the extreme and damaging types of disasters. Tornados, wind, and hail all belong to the category of storms, but only the tornado damage variable has a statistically significant on GDP levels and growth, even when the full amount of FEMA aid is not controlled for. Consistent with state level findings on government aid, the FEMA Public Aid assistance program spending for tornado, hail, and wind damage is capable of having a positive impact on the county economy in terms of both output levels and growth rates.

The state level regressions may not reflect this negative impact of tornado damage because the state is has greater geographic diversification and can take advantage of their productive capacity in areas not impacted by tornados. The impact of tornado damage may also be lost in the aggregation of all types of storms into the category of meteorological disaster.

Conclusion

Examining the county and state level impacts of natural disasters on economic growth and output in the U.S. has led to some interesting insights. Consistent with some literature on the country level, I find a negative impact or no impact of natural disasters on state and county and county economies dependent on the type of disaster. In general, I do not find evidence to support the theories for natural disasters being beneficial to growth suggested in the literature review and theory sections of the paper.

Specifically, at the state level, there are no medium run impacts on the level of output from disasters when FEMA obligations are not controlled for. When the level of FEMA obligations are included as a variable, there is a negative, statistically significant impact on output from damage from geophysical disasters and a positive, statistically significant impact from FEMA obligations for these disasters. This suggests that there may be upward omitted variable bias with the exclusion of aid variables in regressions that look at disaster damage and GDP. Specifically, I find that a 10 percent increase in the per capita damage and FEMA aid for geophysical disaster over five years would have led to a 0.3 percent decrease and a 0.4 increase on GDP per capita respectively, all else equal. In general, the effect of disasters on state output in the medium run for the U.S. is fairly small. Compare this result to Raddatz (2009) who finds that climatic events, on average, decrease GDP per capita by 2% at the country level, though geological impacts were not statistically significant.

When looking at effects on growth from natural disasters at the state level, I find that for the period from 1970-2000, climatological and geophysical disasters have a small, negative effect on the average five year growth rate, even when the level of FEMA aid was not controlled for. This negative effect seems to disappear in the later years (1989-1999), and the coefficients for the disaster variable remain statistically insignificant, even when FEMA aid is controlled for. This may be due to developments in disaster mitigation that have made economies better equipped recovery, but further research on the topic is needed. In general, the shocks to physical capital from disasters seem to have a greater impact on growth rates than shocks to population in the medium term.

There is also evidence that natural disasters may have a greater impact on the per capita GDP of smaller areas. When looking at tornado damage at the county level, I find a negative and statistically significant effect on both output levels and growth rates over five years, even for the most recent years 1999-2009. The effect is small, however, and negative. Specifically, a 10 percent increase in per capita economic loss from tornados over five years would have led to a 0.29 percent drop in the per capita GDP of the county, all else equal. The median amount of tornado damage over five years would have led to a small, 0.000137 percentage point drop in the average GDP growth rate, all else equal. Compare this with Strobl (2008) who find that counties in the U.S. that are struck by hurricanes will see a 0.8 percentage point drop in growth rate in the year of the event. FEMA Public Aid has a small, positive effect on both output and growth rate. A 10 percent increase in per capita aid over five years would have led to a 0.083 percent increase in output, all else equal and the median amount of aid (when granted) would have led to a 0.00022 percentage point increase in the growth rate over five years. The county level results also support the idea that different disasters have different effects on the economy. Consequently, information may be lost in aggregation. Tornados are categorized under the umbrella of meteorological disasters, which do not have an impact on GDP at the state level. Graph 10 shows that the average amount of per capita tornado damage is increasing from the years 1999-2009, but remains fairly steady. In contrast, annual damage attributable to hail and wind is much more erratic. This suggests a certain regularity to tornados that could contribute to their negative economic impact by discouraging investment or adoption of expensive new technology during reconstruction. Furthermore, damage from tornados is generally greater than damage from hail and wind. However, much more research would be needed to make these claims, and it would provide an interesting area to explore for further research.

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Tables

Table 1. Fixed Effects Level Regressions with Economic Loss, 1970-2000

Dependent Variable	Ln of Real Per Capita GDP							
	Without FEMA Dummy Variable				With FEMA Dummy Variable			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Per Capita Capital Stock	0.585***	0.582***	0.590***	0.585***	0.684***	0.681***	0.690***	0.685***
	[6.916]	[6.867]	[6.937]	[6.926]	[6.479]	[6.420]	[6.496]	[6.505]
Human Capital Variable	0.0243***	0.0246***	0.0242***	0.0245***	0.0295***	0.0297***	0.0292***	0.0296***
(Percent of Bachelor's Degrees or Higher in Population 25 years or older)	[7.283]	[7.224]	[7.076]	[7.230]	[7.111]	[7.044]	[6.856]	[7.064]
HIT variable for Climatological	0.00284				0.00131			
(Previous 5 years)	[1.237]				[0.796]			
HIT variable for Geophysical		-0.00410				-0.00396		
(Previous 5 years)		[-1.103]				[-1.628]		
HIT variable for Hydrological			65.68				58.01	
(Pervious 5 years)			[0.892]				[0.915]	
HIT variable for Meteorological				-5.309				-5.872
(Previous 5 years)				[-0.274]				[-0.481]
Dummy Variable for FEMA					-0.0663***	-0.0663***	-0.0655***	-0.0667***
(1980 or Later)					[-6.672]	[-6.793]	[-6.701]	[-6.821]
Constant	3.824***	3.842***	3.773***	3.818***	2.767***	2.796***	2.708***	2.757***
	[4.777]	[4.788]	[4.690]	[4.779]	[2.760]	[2.779]	[2.688]	[2.759]
Observations	1,632	1,632	1,632	1,632	1,632	1,632	1,632	1,632
R-squared	0.924	0.924	0.924	0.924	0.922	0.922	0.922	0.922

Notes: Robust t-statistics in brackets. All variables are in natural logs.
*** p<0.01, ** p<0.05, * p<0.1

Table 2. Fixed Effects Level Regressions with Human Loss, 1970-2000

Dependent Variable	Ln of Real Per Capita GDP							
	Without FEMA Dummy Variable				With FEMA Dummy Variable			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Per Capita Capital Stock	0.531*** [8.239]	0.533*** [7.534]	0.523*** [7.835]	0.517*** [7.580]	0.599*** [7.405]	0.598*** [6.993]	0.593*** [7.193]	0.593*** [6.968]
Human Capital Variable (Percent of Bachelor's Degrees or Higher in Population 25 years or older)	0.0244*** [8.672]	0.0243*** [7.641]	0.0247*** [8.363]	0.0248*** [8.584]	0.0298*** [9.323]	0.0299*** [8.398]	0.0301*** [9.124]	0.0301*** [9.056]
AFF variable for Climatological (Previous 5 years)	19.30* [1.918]				11.53* [1.983]			
AFF variable for Geophysical (Previous 5 years)		22.24 [1.080]				8.569 [0.600]		
AFF variable for Hydrological (Previous 5 years)			1.503* [1.847]				0.505 [0.710]	
AFF variable for Meteorological (Previous 5 years)				0.648 [1.277]				0.0641 [0.140]
Dummy Variable for FEMA (1980 or Later)					-0.0614*** [-5.691]	-0.0619*** [-5.678]	-0.0617*** [-5.704]	-0.0618*** [-5.897]
Constant	4.372*** [7.143]	4.358*** [6.518]	4.455*** [7.047]	4.512*** [6.968]	3.623*** [4.647]	3.631*** [4.424]	3.682*** [4.642]	3.684*** [4.505]
Observations	1,632	1,632	1,632	1,632	1,632	1,632	1,632	1,632
R-squared	0.935	0.935	0.935	0.935	0.933	0.933	0.933	0.933

Notes: Robust t-statistics in brackets. All variables are in natural logs.
*** p<0.01, ** p<0.05, * p<0.1

Table 3. Fixed Effects Growth Regressions with Economic Losses, 1970-2000

Dependent Variable	Per Capita GDP Growth Rate			
	(1)	(2)	(3)	(4)
Growth of Capital Stock	0.809***	0.803***	0.813***	0.813***
	[15.27]	[14.58]	[14.28]	[14.35]
Growth of Human Capital	0.0109***	0.0112***	0.0116***	0.0118***
	[3.175]	[3.105]	[3.580]	[3.683]
HIT variable for Climatological Disasters (5 years)	-0.000741***			
	[-5.884]			
HIT variable for Geophysical Disasters (5 years)		-0.000715***		
		[-4.020]		
HIT variable for Hydrological Disasters (5 years)			7.998	
			[1.575]	
HIT variable for Meteorological Disasters(5 years)				-0.875
				[-0.338]
Constant	-0.0292***	-0.0296***	-0.0309***	-0.0312***
	[-4.290]	[-4.142]	[-4.760]	[-4.878]
Observations	357	357	357	357
R-squared	0.606	0.600	0.597	0.595

Notes: Robust t-statistics in brackets. All variables are in natural logs.
Year dummies are included as fixed effects to control for the presence of FEMA but are not reported.
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Fixed Effects Growth Regressions with Human Losses, 1970-2000

Dependent Variable	Per Capita GDP Growth Rate			
	(1)	(2)	(3)	(4)
Growth of Capital Stock	0.811***	0.808***	0.810***	0.814***
	[14.33]	[14.27]	[14.42]	[14.10]
Growth of Human Capital	0.0119***	0.0123***	0.0118***	0.0119***
	[3.741]	[3.650]	[3.665]	[3.613]
AFF variable for Climatological Disasters (5 years)	-1.267**			
	[-2.443]			
AFF variable for Geophysical Disasters (5 years)		2.774		
		[1.076]		
AFF variable for Hydrological Disasters (5 years)			0.237	
			[0.971]	
AFF variable for Meteorological Disasters(5 years)				0.0736
				[1.134]
Constant	-0.0314***	-0.0323***	-0.0312***	-0.0314***
	[-4.965]	[-4.748]	[-4.818]	[-4.800]
Observations	357	357	357	357
R-squared	0.598	0.596	0.597	0.597

Notes: Robust t-statistics in brackets. All variables are in natural logs.
Year dummies are included as fixed effects to control for the presence of FEMA but are not reported.
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Fixed Effects Level Regression with FEMA Obligations and Economic Loss, 1989-1999

Dependent Variable	Ln of Real Per Capita GDP							
	Without FEMA Obligations Variable				With FEMA Obligations Variable			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Per Capita Capital Stock	0.335***	0.346***	0.344***	0.326***	0.311**	0.271***	0.353***	0.326***
	[2.700]	[2.689]	[2.702]	[2.948]	[2.243]	[2.800]	[2.851]	[2.980]
Human Capital Variable	0.129***	0.131***	0.131***	0.131***	0.130***	0.135***	0.131***	0.131***
(Percent of Bachelor’s Degrees or Higher in Population 25 years or older)	[17.99]	[18.21]	[17.75]	[18.90]	[16.88]	[24.08]	[17.93]	[18.85]
HIT variable for Climatological	0.00355				0.00436*			
(Previous 5 years)	[1.491]				[1.754]			
Per Capita Climatological FEMA Aid					-0.00435			
(Previous 5 years)					[-0.810]			
HIT variable for Geophysical		0.00319				-0.0310***		
(Previous 5 years)		[0.633]				[-5.571]		
Per Capita Geophysical FEMA Aid						0.0402***		
(Previous 5 years)						[5.447]		
HIT variable for Hydrological Disasters			-0.00220				-0.00172	
(Previous 5 years)			[-0.347]				[-0.271]	
Per Capita Hydrological FEMA Aid							0.00201	
(Previous 5 years)							[1.071]	
HIT variable for Meteorological Disasters				0.00165				0.00134
(Previous 5 years)				[0.689]				[0.637]
Per Capita Meteorological FEMA Aid								0.00105
(Previous 5 years)								[0.376]
Constant	4.040***	3.892***	3.921***	4.098***	4.264***	4.581***	3.828***	4.104***
	[3.563]	[3.296]	[3.373]	[4.067]	[3.348]	[5.157]	[3.394]	[4.118]
Observations	357	357	357	357	357	357	357	357
R-squared	0.967	0.967	0.967	0.967	0.968	0.970	0.967	0.967

Notes: Robust t-statistics in brackets. All variables are in natural logs.
Year dummies are included as fixed effects but are not reported.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6. Fixed Effects Growth Regression with FEMA Obligations and Economic Loss, 1989-1999

Dependent Variable	Per Capita GDP Growth Rate							
	Without FEMA Obligations Variable				With FEMA Obligations Variable			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Growth of Capital Stock	0.670***	0.678***	0.664***	0.677***	0.698***	0.640***	0.685***	0.672***
	[3.702]	[3.622]	[3.518]	[3.701]	[4.276]	[3.283]	[3.752]	[3.655]
Growth of Human Capital	0.0227***	0.0226***	0.0227***	0.0231***	0.0226***	0.0230***	0.0227***	0.0232***
	[11.87]	[12.68]	[11.69]	[12.59]	[12.26]	[12.37]	[11.87]	[12.11]
HIT variable for Climatological	-0.000140				-0.000419			
(5 years)	[-0.228]				[-0.673]			
Per Capita Climatological FEMA Aid					0.00156			
(5 years)					[0.717]			
HIT variable for Geophysical		0.000855				-0.00362		
(5 years)		[0.638]				[-1.507]		
Per Capita Geophysical FEMA Aid						0.00525*		
(5 years)						[1.952]		
HIT variable for Hydrological Disasters			0.000658				0.000852	
(5 years)			[0.376]				[0.474]	
Per Capita Hydrological FEMA Aid							0.000912	
(5 years)							[1.130]	
HIT variable for Meteorological Disasters				-0.000767				-0.000662
(5 years)				[-1.530]				[-1.223]
Per Capita Meteorological FEMA Aid								-0.000352
(5 years)								[-0.591]
Constant	-0.382***	-0.381***	-0.382***	-0.385***	-0.380***	-0.387***	-0.383***	-0.387***
	[-11.69]	[-12.45]	[-11.40]	[-12.39]	[-12.06]	[-12.16]	[-11.52]	[-12.00]
Observations	357	357	357	357	357	357	357	357
R-squared	0.888	0.888	0.888	0.890	0.888	0.890	0.889	0.890

Notes: Robust t-statistics in brackets. All variables are in natural logs.
Year dummies are included as fixed effects but are not reported.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7. County-Level Fixed Effects Level Regression and Economic Loss, 1999-2009

Dependent Variable	Ln of Real Per Capita GDP	
	(1)	(2)
Capital Stock per capita	0.989***	0.996***
	[89.17]	[93.19]
Human Capital Variable	0.00635***	0.00524***
(Percent of Bachelor's Degrees or Higher in Population 25 years or older)	[4.293]	[3.750]
Dollars of Tornado Damage per capita	-0.0220**	-0.0290***
(Previous 5 years)	[-2.430]	[-3.644]
Dollars of Hail and Wind Damage per capita	0.00310*	0.00300*
(Previous 5 years)	[1.787]	[1.904]
Dollars of FEMA Public Aid per capita		0.00877***
(Previous 5 years)		[9.000]
Constant	-0.204*	-0.273**
	[-1.793]	[-2.494]
Observations	1,799	1,799
R-squared	0.931	0.936

Notes: Robust t-statistics in brackets. All variables are in natural logs.
Year dummies are included as fixed effects but are not reported.
*** p<0.01, ** p<0.05, * p<0.1

Table 8. County-Level Fixed Effects Growth Regression and Economic Loss, 1999-2009

Dependent Variable	GDP Growth Rate	
	(1)	(2)
Growth of Capital Stock	0.699***	0.698***
	[58.93]	[57.97]
Growth of Human Capital	0.0644**	0.0679**
	[2.471]	[2.323]
Dollars of Tornado Damage per capita	-0.00364***	-0.00347***
(5 year total)	[-7.539]	[-6.024]
Dollars of Hail and Wind Damage per capita	0.000305*	0.000290*
(5 year total)	[1.742]	[1.724]
Dollars of FEMA Public Aid per capita		0.000455***
(5 year total)		[2.652]
Constant	0.0277***	0.0190***
	[7.588]	[5.651]
Observations	1,799	1,799
R-squared	0.914	0.915

Notes: Robust t-statistics in brackets. All variables are in natural logs.
Year dummies are included as fixed effects but are not reported.
*** p<0.01, ** p<0.05, * p<0.1

Charts and Graphs

Chart 1. Top 10 States in Total Economic Loss in Current Dollars (1970-2000) from EM-DAT

State	Total	Breakdown			
		Climatological	Geophysical	Hydrological	Meteorological
California	$38,755,606,034	$2,659,554,483	$31,150,200,000	$2,505,930,642	$2,439,920,909
Florida	$28,020,089,511	$1,762,979,476	$0	$0	$26,257,110,035
Texas	$18,282,400,750	$2,392,301,365	$0	$1,666,008,904	$14,224,090,481
Louisiana	$10,903,060,837	$580,053,368	$0	$0	$10,323,007,469
South Carolina	$8,288,824,613	$302,457,220	$0	$0	$7,986,367,393
Illinois	$6,212,520,572	$116,081,757	$0	$4,306,167,825	$1,790,270,990
New York	$5,668,125,143	$171,064,879	$0	$395,419,940	$5,101,640,325
Pennsylvania	$4,462,110,639	$659,826,865	$0	$421,224,739	$3,381,059,035
Missouri	$3,864,857,187	$1,218,851,025	$0	$1,703,657,844	$942,348,318
Virginia	$3,832,954,349	$637,503,443	$0	$41,740,459	$3,153,710,447

Chart 2. Top 10 States in Total Number of Killed and Affected Persons (1970-2000) EM-DAT

State	Total	Breakdown			
		Climatological	Geophysical	Hydrological	Meteorological
Florida	1,010,042	40,944	0	0	969,099
New York	713,020	334	0	41,336	671,351
Pennsylvania	472,809	24	0	30,024	442,761
North Carolina	321,890	13	0	3	321,875
New Jersey	306,929	0	0	22,907	284,022
California	300,004	4,336	57,699	226,730	11,239
Virginia	249,813	12	0	12,482	237,319
Michigan	232,866	19	0	1,253	231,595
Massachusetts	232,732	0	0	13,325	219,407
Maryland	179,500	18	0	9,662	169,820

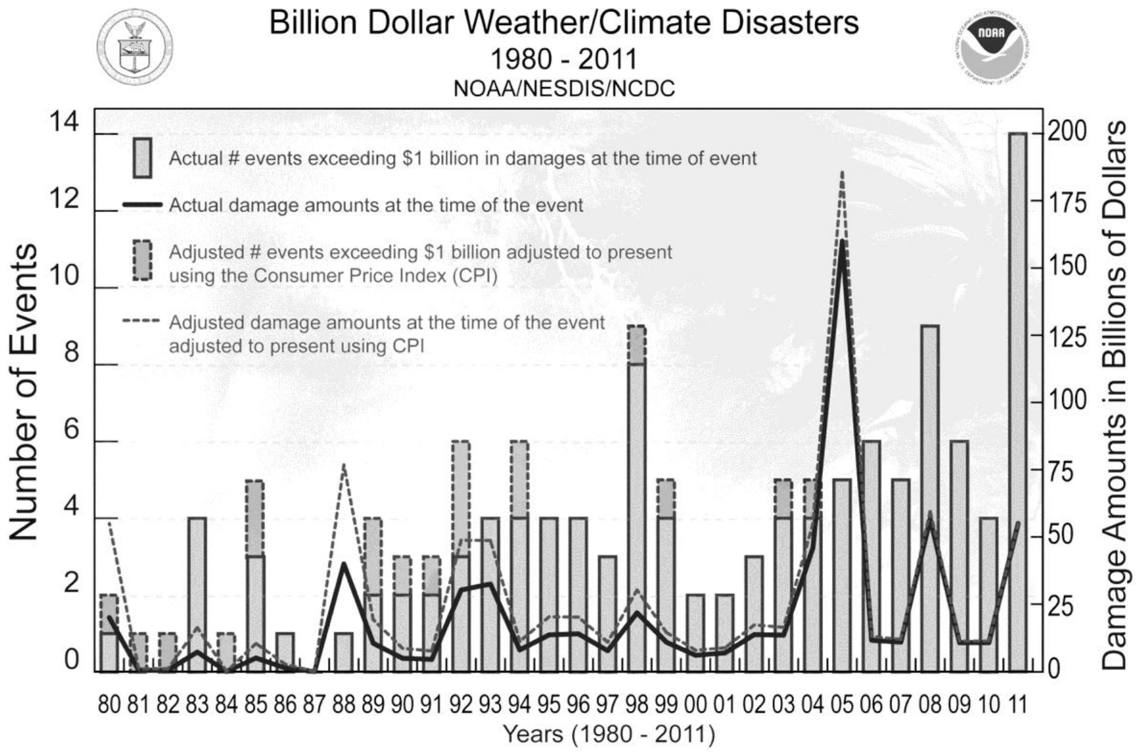
Chart 3. Total Incidents Breakdown (1970-2000)

Climatological		Geophysical		Hydrological		Meteorological	
Drought	16	Earthquake	15	Mass movement wet	2	Storm	964
Extreme Temperature	58	Volcano	1	Flood	249		
Wildfire	51						
Total	125		16		251		964

Chart 4. Breakdown of Killed and Affected by Disaster Subtype (1970-2000)

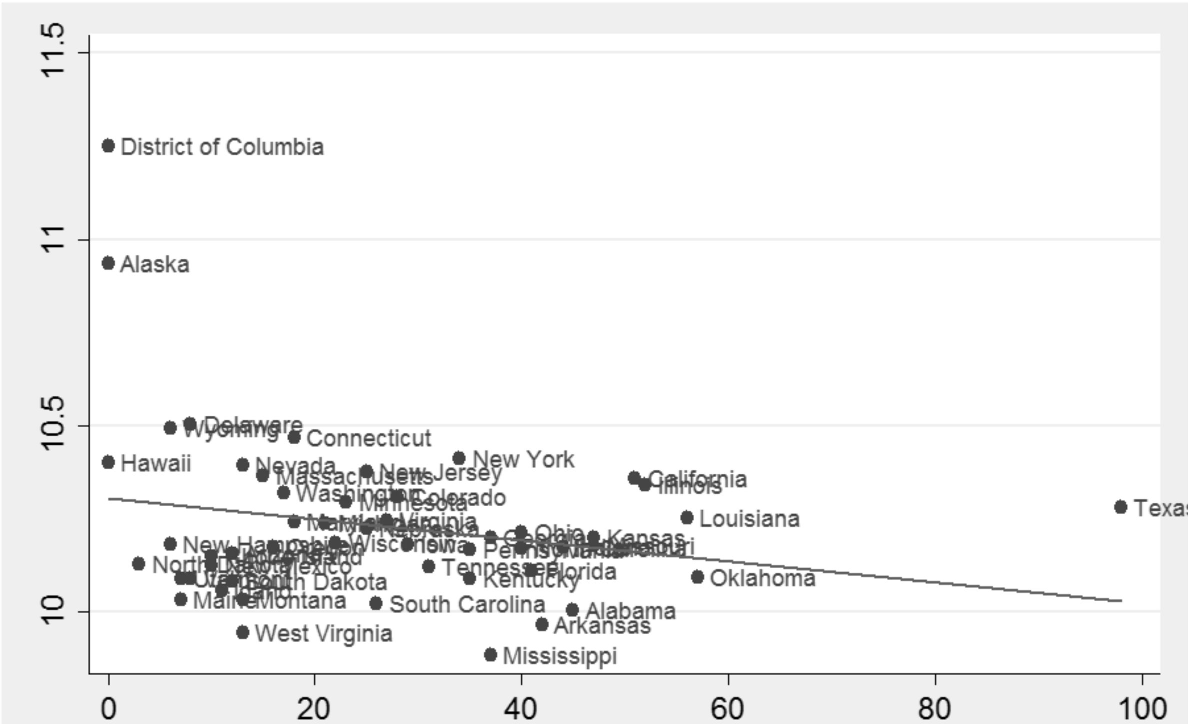
	Killed	**Affected**	**Total**	**Proportion Killed**
Climatological	16239	106867	123106	0.131911
Geophysical	237	63067	63304	0.003744
Hydrological	3585	4706761	4710346	0.000761
Meteorological	24316	49426744	49451060	0.000492

Graph 1. Damage Amounts and Number of Events in the U.S. 1980-2011



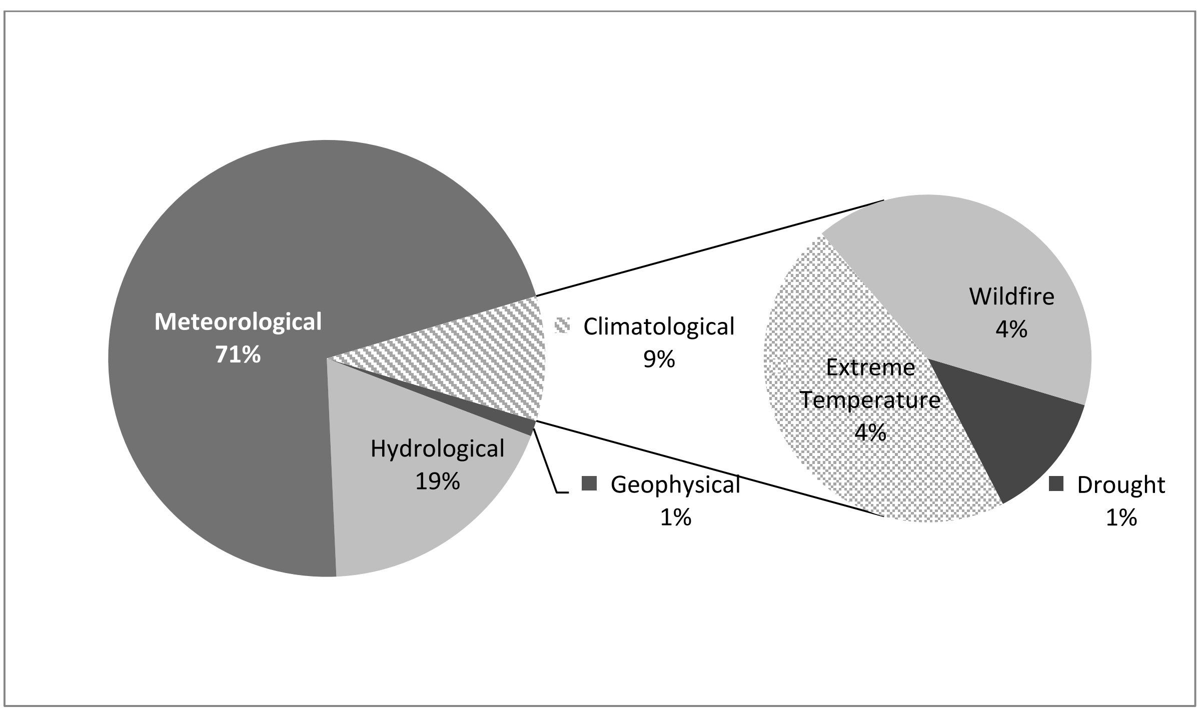
Source: www.ncdc.noaa.gov

Graph 1. Total Number of Disasters and Ln(Average Per Capita GDP) from 1970-2000

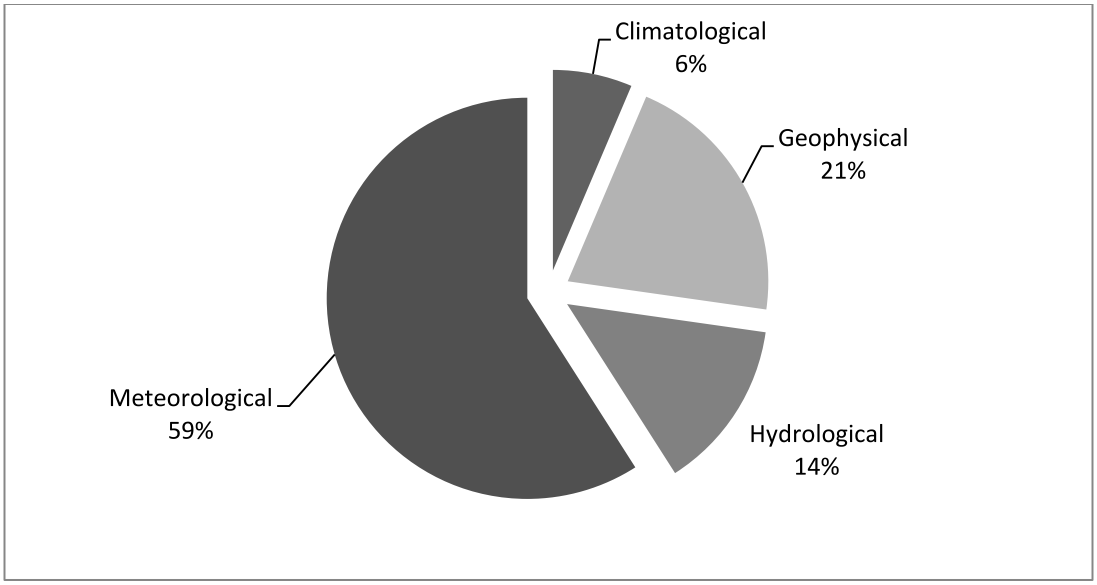


Total Disasters 1970-2000

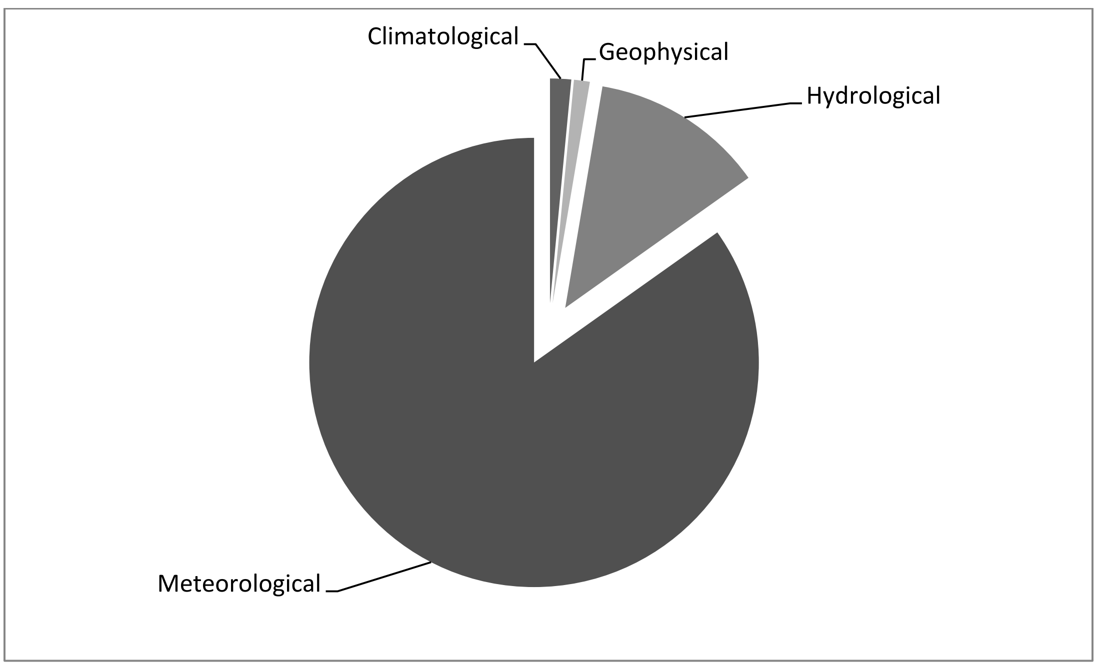
Graph 2. Total Incidents with Climatological Breakdown (1970-2000)



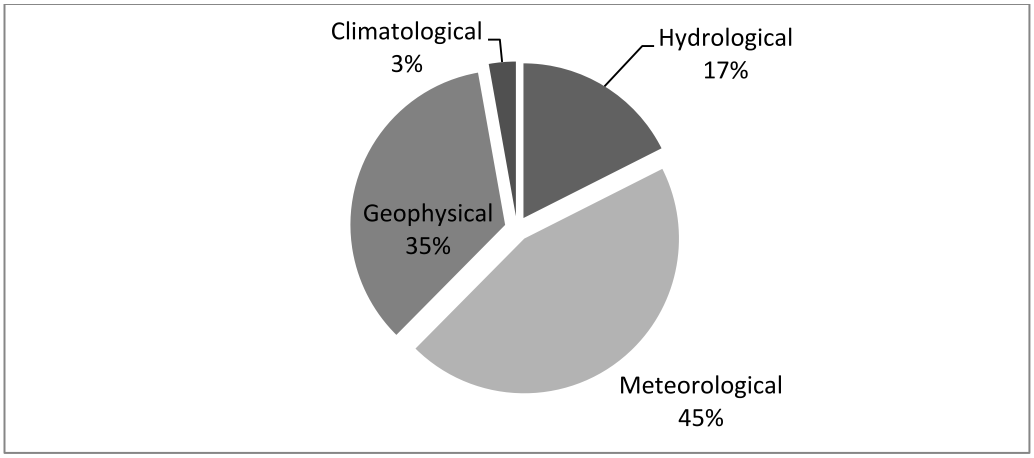
Graph 3. Total Economic Damage Breakdown in Current Dollars (1970-2000)



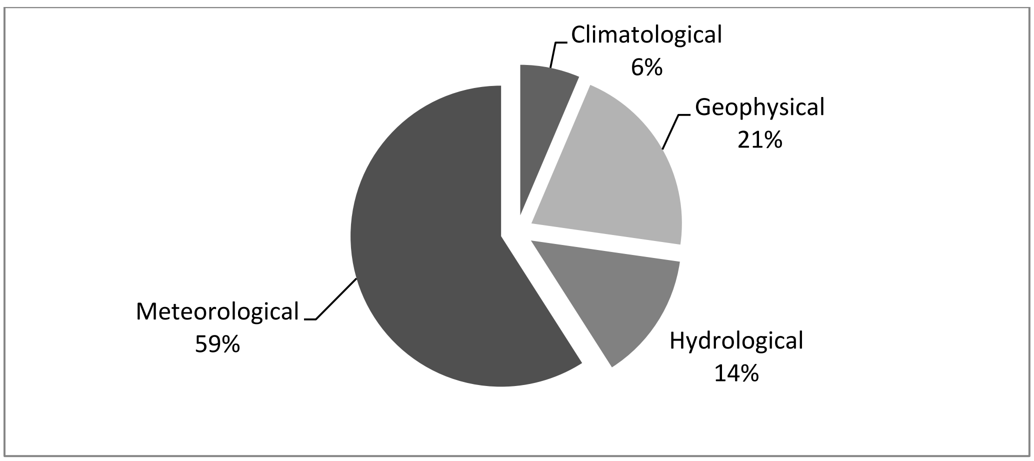
Graph 4. Total Persons Killed and Affected Breakdown (1970-2000)



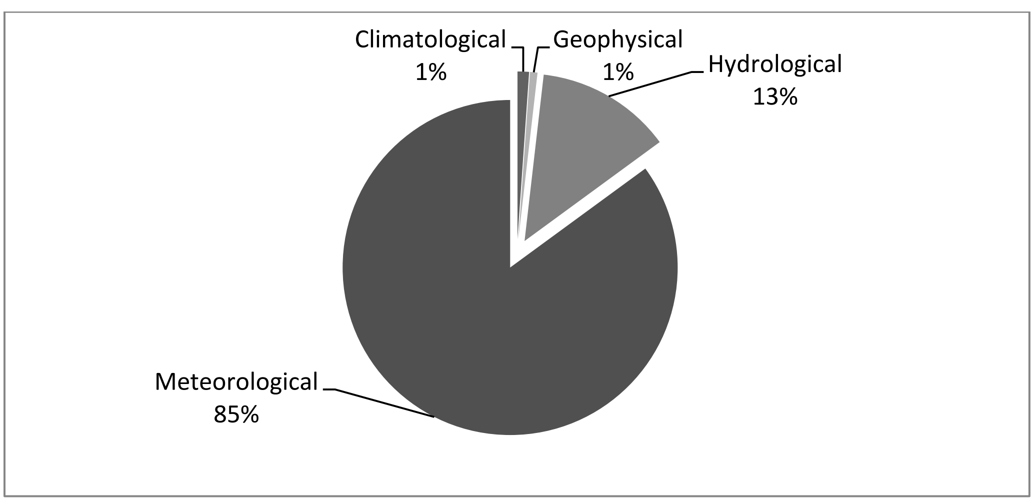
Graph 5. Breakdown of Total FEMA Obligations (1989-1999)



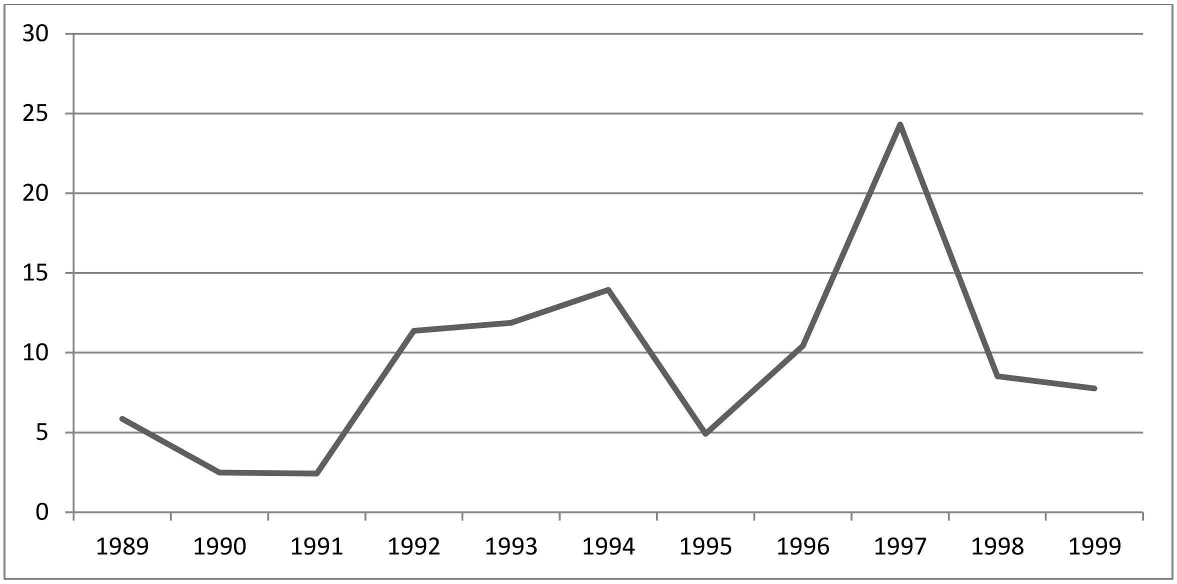
Graph 6. Total Economic Damage Breakdown in Current Dollars (1989-1999)



Graph 7. Total Persons Killed and Affected Breakdown (1989-1999)

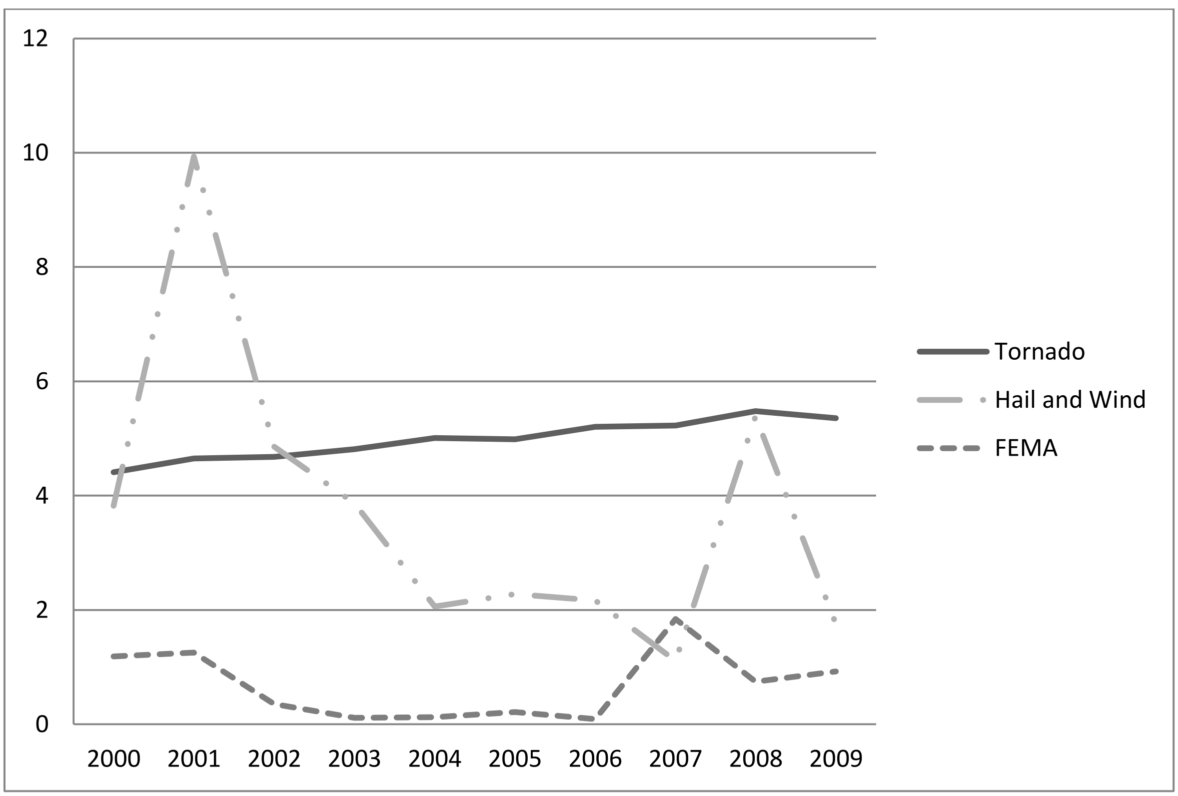


Graph 8. Average State Per Capita FEMA Total Obligations (1989-1999)



Note: Values are in 2005 dollars

Graph 9. Average County Per Capita Damage and FEMA Public Aid (1999-2009)



Note: Values are in 2005 dollars

Appendix

Appendix Table A. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
State Per Capita GDP	1836	27312.82	10898.67	11000.24	114814
State Per Capita Capital Stock	1836	25602.37	7831.58	10336.33	69116.49
State Human Capital Variable (Percent of Bachelor’s Degrees or Higher in Population 25 years or older)	1728	16.29595	5.645582	4.65	33.19
State Per Capita Economic Loss (over 5 years)					
Climatological	1632	8.032687	46.7076	0	985.8272
Geophysical	1632	5.408908	65.6989	0	1069.839
Hydrological	1632	1.02E-05	0.000053	0	0.000577
Meteorological	1632	67.88058	278.3001	0	2962.343
State Proportion of Population Killed or Affected (over 5 years)					
Climatological	1632	1.88E-05	0.000392	0	0.014663
Geophysical	1632	8.59E-06	7.81E-05	0	0.000879
Hydrological	1632	0.000562	0.005385	0	0.094035
Meteorological	1632	0.001472	0.005959	0	0.038982
State Per Capita FEMA Obligations (over 5 years)					
Climatological	357	1.269349	5.196441	0	44.74274
Geophysical	357	4.186398	32.71135	0	277.9459
Hydrological	357	19.52499	80.00825	0	933.5169
Meteorological	357	25.83937	44.56667	0	292.6099

Appendix Table B. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
County Per Capita GDP	2827	16272.36	6298.672	4384.53	70291.98
County Per Capita Capital Stock	2827	21572.06	9250.408	5330.777	94108.2
County Human Capital Variable (Percent of Bachelor's Degrees or Higher in Population 25 years or older)	2827	16.45815	5.776185	6.02222	51.525
County Per Capita Tornado Damage (over 5 years)	1799	24.64877	133.5703	0	1732.816
County Per Capita Hail and Wind Damage (over 5 years)	1799	19.78589	119.4179	0	2816.951
County Per Capita FEMA Public Aid (over 5 years)	1799	2.630958	6.024143	0	81.56701

Appendix Table C. Median Statistics (all values are natural logs)

Time Period	Median Values (for non-zero observations)					
	HIT Variable		AFF Variable		Per Capita FEMA Obligations	
1970-2000	Climatological	3.31	Climatological	1.27e-5		
	Geological	3.76	Geological	6.1e-5		
	Hydrological	3.12	Hydrological	2.42e-4		
	Meteorological	4.99	Meteorological	6.69e-5		
1989-1999	Climatological	2.23	Climatological	1.57e-5	Climatological	0.74
	Geological	1.42	Geological	8.59e-4	Geological	2.83
	Hydrological	1.69	Hydrological	2.24e-4	Hydrological	2.24
	Meteorological	4.33	Meteorological	3.9e-5	Meteorological	2.71
1999-2000	Damage Per Capita				FEMA Public Aid Per Capita	
	Tornado	0.0394			Tornado, Hail, and Wind	0.4836
	Hail and Wind	5.26e-5				

Appendix Table D. Detailed EM-DAT Disaster Subgroups

Disaster Subgroup	**Definition**	**Disaster**
Geophysical	Events originating from solid earth	Earthquake, Volcano, Mass Movement (dry)
Meteorological	Events caused by short-lived/small to meso scale atmospheric processes (in the spectrum from minutes to days)	Storm, Tornado
Hydrological	Events caused by deviations in the normal water cycle and/or overflow of bodies of water caused by wind set-up	Flood, Mass Movement (wet)
Climatological	Events caused by long-lived/meso to macro scale processes (in the spectrum from intra-seasonal to multi-decadal climate variability)	Extreme Temperature, Drought, Wildfire

Appendix Table E. Correlation Matrix for State Level Damage and Total FEMA Obligations

	Economic Loss			
	Climatological	Geophysical	Hydrological	Meteorological
FEMA Obligation for Disaster	0.1057	0.9955	0.0001	0.8035

Appendix Table F. Correlation Matrix for County Level Damage and FEMA Public Aid

	Tornado Damage	Hail and Wind Damage	FEMA Public Aid for Tornado, Hail, and Wind Damage
Tornado Damage	1		
Hail and Wind Damage	0.0219	1	
FEMA Public Aid for Tornado, Hail, and Wind Damage	0.1513	0.0011	1

Alexander, D. E. (2000). *Confronting Catastrophe: New Perspectives on Natural Disasters*: Oxford University Press.