Weather or Wealth: An Analysis of Property Loss Caused by Flooding in the U.S.

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Abstract

Using fine-scale climate process, we investigated the relationship between extreme surface water runoff and property damages caused by flood in the U.S. Special attention was paid to disentangle effects of extreme weather and social wealth accumulation. We find it is still premature to claim that extreme weather events becomes more destructive due to anthropological climate change, if take into account the increasing values exposed to natural hazards.

1 Introduction

Natural science studies suggest a shift toward the period of increased extreme precipitation and potential flood disasters in multiple regions (Alexander et al., 2006; Moberg et al., 2006; Easterling et al., 2000; Kunkel et al., 1999). But much less has been done on the consequences of this change. The lack of progress can be attributed to several reasons. First, the translation from hydrologic floods to damaging floods is not straightforward. The two differ in that a hydrologic flood occurring in an unpopulated area may cause no damage. Flood disasters are therefore the result of the interaction of hydrologic floods and societal systems (e.g., location choice and mitigation policy). The latter, however, is complex and its function cannot be observed directly. Second, it is hard to make a statement about the attribution of flood disasters. Although some argue that anthropogenic climate change has led to increasing loss probabilities (Höppe and Grimm, 2008;

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Schmidt et al., 2009), others find no evidence for such a trend (Neumayer and Barthel, 2011). Instead, they believe increasing exposure due to population and economic growth has been a much more significant factor driving the results (Pielke et al., 2005; Barredo, 2009). Last, the role of development in mitigation has not been identified in a uniform manner so far. While there was a seeming consensus that the risk of damages from disasters is monotonically decreasing in income (Kahn, 2005; Toya and Skidmore, 2007), recently studies find a non-monotonic inverted-U type relationship between development and disaster damages (Kellenberg and Mobarak, 2008).

The purpose of this study was to disentangle effects of contributing factors to flood-caused property loss. It is distinct from previous studies in two aspects. First, instead of using average or total annual precipitation, daily based climate process is used to better describe surface water runoff peak and how destructive a flood can be. Second, the analysis is done at county level and extended to all the US counties. In flood analysis, the conflict between hydrologic and social-economic boundaries makes it not easy to pick the appropriate research unit. To get around this issue, we find the location of USGS hydrologic monitoring stations and link the sites with U.S. counties in ArcGIS 10.

2   Conceptual Framework

Expected loss has been defined as being conceptually equivalent to the risk of exposure to a particular hazard for a given area and reference period. Based on mathematical calculation, it is the product of hazard, exposure and vulnerability (Downing et al., 1999; Kron, 2005).

$$Risk = Hazard \times Exposure \times Vulnerability$$

A hazard is a threatening event, or the probability a potentially damaging phenomenon occurs within a given time period and area; exposure is the values at risk, including property and humans that are present at the location involved; vulnerability is the degree of loss resulting from a potentially damaging phenomenon (DHA, 1993; Kron, 2005). These definitions highlight several features of flood-induced loss.

First, flood risk is always concerned with time and location. Results could be very sensitive to the

time interval (day, month, quarter, year) and the unit of observation (river basin or socio-economic unit such as community, county and state) chosen for the analysis. High resolution data definitely reveal more details, but meanwhile raise the level of computational sophistication and often confronted with the issue of data availability. The focus of this paper will be at annual county level since this appears to be the most meaningful socio-economic and decision-making unit. This choice also stems from the the consideration of data availability.

Second, flood risk is evolutionary rather than static. Three components of risk assessment will evolve over the course of decades or more. For example, individuals abatement reduces vulnerability, but location choices increase the value exposed to disaster. The interaction of the two can introduce a inverted-U shape relationship between development and risk, as found by Kellenberg and Mobarak (2008). On the hazard side, the probability density function tails fattened by the structural uncertainty of climate extremes may have a big effect on risk analysis (Weitzman, 2009). Future damages will be different from predictions based on present hazard-loss relationships. In other words, the evolving nature of risk requires an extended, dynamic framework.

3 Data

3.1 Property loss caused by flooding

The damage data are pulled from the National Climatic Data Center (NCDC) storm events database. Estimated property damage was recorded by event, along with starting date and location. In the present research, only summer storm (June to August) was considered. The period 1980-2009 was selected because of limitations in the stream flow data used in this analysis.

Figure 1 depicts the annual damage density ($1000\$/mi^2$) during this period. Damage levels are converted into densities so that the loss can be compared regardless of county size. The amount of damage is inflation-adjusted, using 2011 as a CPI base year. According to the map, regions that suffer most from flooding mainly concentrate in Midwest and Northeast US. Figure 2 contains two sets of trend plots that show damages since 1980s'. On the top, the frequency of damage due to flooding is plotted. It's worth to note that a significant jump occurred between year 1992 and 1993. Possibly, it was caused by improved reporting system. If so, we need to use the data with caution.

3.2 Hazard

In this research, an improvement over the previous ones is the emphasis of extreme precipitation events. To serve the purpose, maximum daily stream flow observed at each weather station was used. Data were downloaded from the USGS National Water Information System. We believe this measurement of hazard is superior to the broadly-used total or average precipitation in two ways. First, it permits us to separate the hazardous precipitation events from the non-hazardous ones. Second, the stream flow is determined based on precipitation plus surface conditions (soil type and vegetation), slope and human impacts (dams and irrigation withdraw), etc. The degree of hazard may be changed by these non-precipitation factors.

Extreme event is defined as water runoff (ft^3/sec) that exceeds the 95th percentile of 30 years (1980-2009) daily observations at each weather station. Only extreme flows are kept and aggregated by station over the season. Among all the 21,927 stations, over 95% have records for the whole year and do not have any missing days.

4 Method

4.1 Reconcile geographic and socio-economic unit

One of the barriers prohibiting disaster analysis is that geographic and socio-economic boundaries are rarely the same. One of them must be manipulated to "fit" the other. In our case, since usually more than one hydrologic stations are placed in each county, it is easier to aggregate station data to fit the county contours. To this end, we first use ArcMap to find the stations located in each county. Then we use Inverse Distance Weighted interpolation to calculate the "aggregated" water run off associated with a particular county during the season. The same procedure was then repeated for all the time series.

4.2 Flood damage normalization

In order to separate out "exposure" effect that may drive up the damage, we first ran linear trend tests on inflation-adjusted damage, growth of population and wealth. This analysis was done at national level because related information is not provided for counties. Data series were converted

to normal distribution using the log transformation. The linear trend, if exists, can be translated into annual change rate of exposure. Subtracting it from the growth rate of flood damage will allow the estimation of the size of the other two contributors, namely hazard and vulnerability.

4.3 Fixed effect panel data analysis

Fixed effect is chosen over random effect based on the following two reasons. One is that to overcome the trade-off between data inputs and research scope, many variables such as topographic features, elevation and distance to the nearest river are omitted although they are closely related to the consequences of flooding. Most of these variables are time-invariant or change only slightly during a couple of decades. The fixed effect estimation has the advantage of eliminating the omitted variable bias, but with no need to explicitly include the variables in the model. Another reason is that fixed effect is allowed to be correlated to other regressors, which is a more realistic assumption in our case. Surface water runoff after all should not be independent of topographic features, slope and impact of human activities, etc.

The model is specified as:

$$damage_{it} = (\beta_0 + u_i) + X_{it}\beta + v_{it} \tag{1}$$

i and t are indices for county and year respectively. X_{it} is a set of variables that control for hazard, exposure and vulnerability. In particular, they are extreme stream flow, county population, per capita personal income, per capita unemployment insurance benefits, the total number of damages reported in previous years (i.e. till year $t-1$), and county poverty rate. u_i is the fixed effect. All the variables are log transformed to best approximate a normal distribution.

5 Results

5.1 Controlling for changes in exposure: population and wealth

Linear trend tests on adjusted damage, population and wealth show statistically significant increasing trend for all three variables. The first two columns of Table 1 summarize the trend, along with the derived annual growth rate. Under the assumption that population and wealth accumulation in flood-prone areas have grown at the same rate, 37.7% of the increase in flood damage can be

attributed to exposure growth from 1980 to 2009. This result is pretty small compared to findings in Pielke Jr and Downton (2000). They conducted a similar trend analysis but used a different damage dataset and looked at a different period (1932-1997).

In our data, the dramatic change in damage between 1992 and 1993 is suspected to be the result of better documentation. To exclude the potential reporting bias, we rerun the analysis but only use data since 1993. The result is reported in the next two columns of Table 1. Following the same assumption, 31.4% of the increase in flood damage can be attributed to population growth. The country's net stock of fixed assets and consumer durable goods (in 2011 dollars) has grown at a rate of 3.43%, slightly more rapidly than flood damage. Again, assuming that the nation's wealth in flood-prone areas has grown at the same rate as national wealth, then all of the increase in flood damage can be attributed to the growth in national wealth. These results are quite comparable to Pielke Jr and Downton (2000).

5.2 Panel data analysis

We ran fixed effect linear regression to detect the elasticity of flood damage with regard to each component that appears in the structural model. Estimators, along with heteroskedasticity-robust standard errors are presented in Table 2. All the coefficients have the expected signs and most of them are highly significant. Not surprisingly, higher surface water runoff leads to larger property damage. On average, for every 10% increase of the extreme stream flows, the damage goes up by 1.7%. For example, the annual property damage caused by summer storm amounts to about 7.8 billion US dollars since 1993. Given a 10% increase of the hazard, it is expected to see an additional 0.13 billion dollars damage each year, assuming exposure and vulnerability remain unchanged.

Wealth and population growth, compared with natural hazard, can contribute much more to the increasing property damage due to flooding. In particular, unit population elasticity of damage implies that population growth matches disaster loss growth. Damage is even more elastic with respect to wealth accumulation, which is approximated by the increase of per capita personal income.

County poverty rate is adopted as a proxy of vulnerability. Ceteris paribus, vulnerable population is associated with potentially larger natural disaster-induced losses. The rest two variable, per capita

6

unemployment insurance benefits and damage in the past are included to control for mitigation activities. Counties that provide good unemployment insurance are more likely to provide other social security benefits and services to prevent hazards from turning into disasters, and keep the damage under controlled once disaster occurs. Flooding experienced in the past teaches people how to prepare for hazardous events and tends to lower expected damages.

6   Discussion

We examine the trend of flooding-induced property damage in the U.S. and attempt to disentangle different disaster dimensions, namely hazard, exposure and vulnerability. Population and wealth expansion are used to normalize damages in previous years. The normalization sheds some light on how destructive a past disaster is if it occurs today. Such a treatment allows us to compare damages across time series and detach exposure effect from total damage. Based on data from past two decades, we find that population growth may explain about one third of the increasing flood loss. Besides, annual growth rate of flood damage matches wealth accumulation, indicating that all of the increase in flood damage can be attributed to the growth in national wealth. According to these results, probably it is still premature to conclude that climate change has led to increased disaster damages. However, our calculation does not take into account mitigation measures that have being taken and effectively reduce local vulnerability, due to lack of related information. Without these mitigation measures, climate impacts on economy can be much more sizable if the measures have been playing significant roles in reducing losses.

In panel data analysis, we find that exposure (approximated by population and per capita income) and hazard (represented by seasonal surface water runoff) explains increasing damages, but the former is a much more important driver than the latter. In addition, counties that have seen floods frequently in the past tend to suffer less from the disaster, possibly due to better flooding preparedness[1]. The external effect of government-provided benefits and services somewhat protect the public by downsizing the damages. Finally, other things being equal, the poor who are more vulnerable to natural hazards are likely to lose more when hit by the extreme precipitation events.

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[1]Another possible explanation is that small disaster events are dominant in the data.
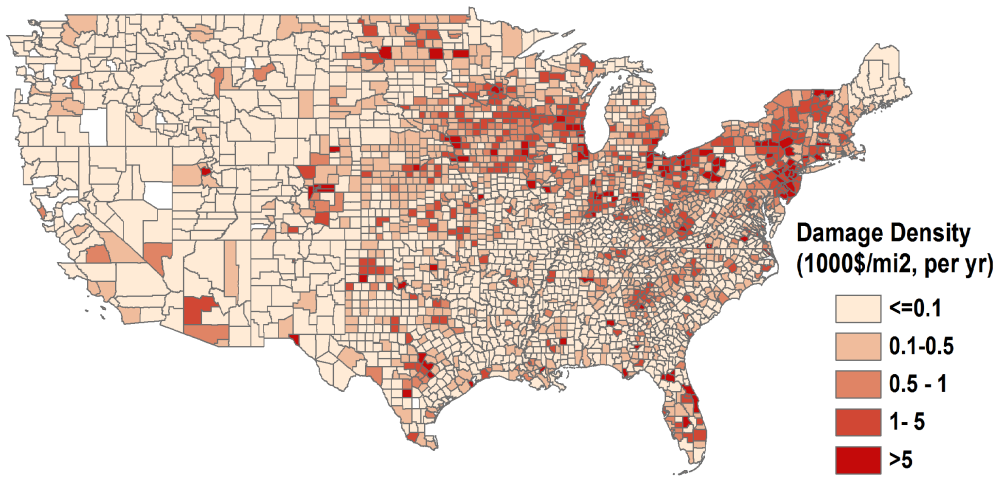
Figure 1: Damage density per year, 1980-2011

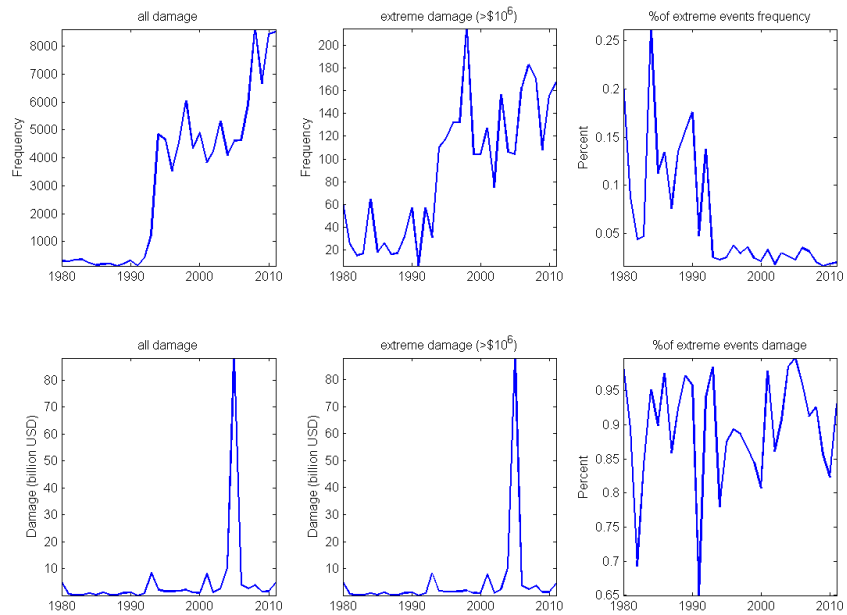Figure 2: Magnitude and frequency of property damage by year, 1980-2011

Table 1: Rate of change in flood damage and exposure indicators

Variable	1980-2009		1993-2009	
	Linear trend	Annual rate of change	Linear trend	Annual rate of change
Total annual flood damage, infation-adjusted	0.087 *	9.14%	0.033 *	3.31%
Population	0.011 *	1.09%	0.010 *	1.04%
Net stock of fixed assets and consumer durable goods	0.023 *	2.36%	0.034 *	3.43%

Dollar estimates are in 2011 US dollars.
* Statistically significant ($\alpha = 0.01$).

Table 2: Data description, 1993-2009

Variable	Mean	Standard Deviation
Inflation-adjusted flood damage, $million$\$	3	91391.5
Seasonal extreme stream flow, ft^3/sec	127054	797120.6
Per capita personal income, \$	32293	7859.5
Population	156636	353494.9
Frequency of damage in previous years	22	24.5
Per capita unemployment insurance benefits, \$	147	124.4
Poverty rate, %	14	5.6

Table 3: Fixed effect linear regression, 1993-2009

Variable	Coefficient	Standard Error
Extreme stream flow	0.17 **	0.012
Per capita personal income	2.05 **	0.338
Population	1.09 **	0.377
Frequency of damage in previous years	-0.23 **	0.042
Per capita unemployment insurance benefits	-0.18 **	0.048
Poverty rate	0.27 *	0.129

Statistically significant (**$\alpha = 0.01$, *$\alpha = 0.05$).

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