Climate Adaptation: Evidence From Extreme Weather

(Preliminary draft)

Stephie Fried*[1] and Tamara L. Sheldon†‡[2]

[1]Department of Economics, Carleton College

[2]Department of Economics, University of South Carolina

December 5, 2016

Abstract

As climate change progresses and the frequency of extreme weather events increases, will agents be able to adapt to reduce the associated damage? This paper develops a two-part strategy to quantify the existing level of extreme weather adaptation and its contribution to the reduction in damage across U.S. counties. First, we estimate the relationship between the frequency of extreme weather events and damage. Second, we use our empirical estimates to calibrate a simple dynamic model that relates frequency and damage to adaptation. From this calibrated model, we quantify the level of adaptation and its effects on damage. We find that even in the most event-prone areas, adaptation investments are relatively small and reduce the damage from extreme weather by less than ten percent.

*sfried@carleton.edu

†Tamara.Sheldon@moore.sc.edu

‡We thank Betty Daniel, Matt Goldman, Travis Warziniack and participants at the 2016 AERE Summer Conference for helpful comments.

1 Introduction

The frequency and severity of extreme weather events are likely to increase over time as a result of climate change (IPCC, 2000; IPCC, 2014). These events often involve large costs; for example, the average property damage from a tornado in the U.S. is almost 1 million in 2010 dollars. As climate change progresses and the frequency of these events increases, will regions be able to adapt to reduce the accompanying damage?

The analysis of climate adaptation is inherently difficult because we do not have comprehensive data on quantities of adaptation capital such as storm drains, snow plows, wind-resistant garage doors, etc. The absence of this data implies that we cannot directly observe the existing amount of adaptation or its effectiveness. The main contribution of this paper is to develop a two-part strategy that allows us to quantify the existing level of extreme weather adaptation and its effects on damage across U.S. counties. First, we estimate the relationship between the frequency of extreme weather events and damage, two variables that we can observe in the U.S. data. Second, we use our empirical estimates to calibrate a simple dynamic model that relates frequency and damage to adaptation. From this calibrated model, we can quantify the level of adaptation and its effects on damage. We find that even in the most event-prone areas, adaptation investments are relatively small and reduce the damage from extreme weather by less than ten percent. These small magnitudes suggest that it is difficult for counties to adapt to extreme weather, making carbon abatement an even more important component of climate change mitigation.

We first estimate the effect of an increase in the frequency of a particular category of extreme weather (such as floods) on the associated damage relative to GDP across U.S. counties and time. Our empirical specification controls for the severity of the weather event and includes county, year, and month fixed effects. Thus, our identifying variation comes from within county changes in frequency and damage over time. The main data are from the National Climatic Data Center's (NCDC) storm events database, which reports event-level information on many types of extreme weather. We focus explicitly on floods, hail, tornados, wind, and winter weather; the five weather categories with the most accurate measures of severity.

Our estimation results reveal that increases in the frequency of extreme weather significantly reduce the damage from floods, tornados, and winter weather events.[1] We hypothesize that the reason for this negative relationship is that increases in frequency increase the perceived probability of future events, which raises the returns to adaptation investments. For example, following a devastating tornado in May of 2013, Moore Oklahoma voted to upgrade its building codes to make residential structures more wind resistant.[2] Similarly, after the severe flooding caused by Superstorm Sandy, New York City announced a 20 billion dollar investment for building flood walls, levees, dune systems and other forms of coastline protection.[3]

In the second part of our analysis, we extend a simple growth model to quantify the links between frequency, adaptation, and damage. We analyze an economy that periodically experiences extreme weather events. These events cause damage, which lowers output. However, agents can invest in a special type of capital, called adaptation capital, to reduce their damage from extreme weather. We calibrate the model parameters from our empirical estimates of the effects of an increase in frequency on damage for the three weather categories with statistically significant coefficients estimates, floods, tornados, and winter. Our calibration is in itself a contribution and implies substantial diminishing returns to the fraction of adaptation capital, relative to total capital. The curvature parameter governing the effect of adaptation capital on damage is considerably less than unity, ranging from 0.48 in the case of floods to 0.62 in the case of tornados. Understanding the diminishing returns to adaptation is important for integrated assessment models which incorporate adaptation

[1] The frequency coefficient estimates for hail and wind events are also negative, but they are not statistically significant.

[2] "Moore adopts new building codes; first city in nation to address tornado impact on homes" News Release, March 17-2014; "An Oklahoma Suburb, Tornado Ready" New York Times, May 14, 2015.

[3] "Mayor Bloomberg Outlines Ambitious Proposal to Protect City Against the Effects of Climate Change to Build a Stronger, More Resilient New York" New York City Press Release PR-201-13, June 11, 2013.

as a component of climate policy.[4]

We use our calibrated model to quantify adaptation capital across U.S. counties with different susceptibilities to extreme weather and its contribution to the reduction in damage. We find that the percent of total capital used for adaptation in counties with the average event frequency ranges from 4.86e-06 percent in the case of tornados to 1.74e-04 percent in the case of floods. If all U.S. counties experienced the average frequency of events, then the total value of adaptation capital in each weather category would be less than 100 million in 2014 dollars. These tiny adaptation investments reduce the damage from extreme weather by under one percent.

Even in the most event-prone regions, where frequency equals its maximum value in the sample, we still find that adaptation investments are very small and have minimal effects on damage. For example, when frequency equals its observed maximum, adaptation capital for winter weather events is only 0.32 percent of total capital, reducing the associated damage by 5.7 percent. Similarly, adaptation capital for tornados is only 0.48 percent of total capital, reducing the associated damage from a tornado by 3.6 percent.[5] The results in these most event-prone regions are an upper bound on the existing level of adaptation capital and its effect on damage.

This paper builds on a previous line of literature that looks for evidence of adaptation from differences in the effects of extreme weather across regions, time, or both. Like the present paper, this earlier work assumes that more frequent exposure to extreme weather creates stronger incentives to adapt, and thus leads to smaller damage.

Much of this earlier literature finds that differences in the frequency of extreme weather events do not lead to significant differences in the damage from extreme weather, suggesting little to no adaptation. In particular, Deschenes and Greenstone (2011) find heterogeneity in

[4]See for example, Barrage (2015); Felgenhauer and Webster (2013); Agrawala et. al. (2010); Agrawala et. al. (2011); De Bruin, Dellink, and Tol (2009); Toll (2007).

[5]Note that while adaptation capital represents a larger fraction of total capital for tornados than for winter weather, it leads to a smaller percentage reduction in damage because the curvature parameter governing the effectiveness of adaptation capital is different for tornados and winter weather.

the response of mortality to temperature in different U.S. regions, but this heterogeneity is not systematically related to the average temperature in those regions. Similarly, Dell, Jones, and Olken (2012) and Schlenker and Roberts (2009) estimate the impact of temperature on economic growth and crop yields, respectively, across different regions and find little evidence that hot regions experience systematically different responses to extreme heat than cold regions. Likewise, Burke, Hsiang, and Miguel (2015) use global data to estimate the relationship between annual economic growth and annual average temperature over two time periods, 1960-1989 and 1990-2010, and find similar effects in each. Finally, Hornbeck (2012) compares the effects of large dust storms on agricultural productivity in the Great American Plains in 1940 (right after the "Dust Bowl" years) and in 1992 and again finds little difference between the two time periods.

Unlike the earlier work on temperature and dust storms, previous literature does find some evidence of adaptation to cyclones. Hsiang and Narita (2012) estimate the impacts of tropical cyclones across areas with different cyclone climatologies and find that the marginal effect of an increase in cyclone wind speed is lower in areas that more frequently experience cyclones with high wind speeds. Similarly, Bakkensen and Mendelsohn (forthcoming) find that countries with more previous cyclone experiences have lower cyclone damage.

Similar to the previous literature, our paper looks for evidence of adaptation from within county variation over time in the frequency and damage from extreme weather events. However, we focus our analysis on floods, hail, tornados, wind, and winter weather events instead of on temperature, dust storms, or cyclones. We then go beyond earlier work and use our estimates to calibrate a quantitive model of adaptation investment. Using the calibrated model, we are able to quantify the proportion and effectiveness of adaptation capital for the different categories of extreme weather. While we find statistically significant evidence of adaptation in the case of floods, tornados, and winter weather events, the magnitudes of the adaptation capital and their associated effects on damage are very small.

The paper proceeds as follows: Section 2 develops the empirical model and the associated predictions. Section 3 describes the data sets and variable construction and Section 4 presents the empirical results. Section 5 develops and calibrates the model and Section 6 uses the calibrated model to quantify the level and effectiveness of adaptation. Section 7 concludes.

2 Empirical specification

We estimate the effects of an increase in the frequency of extreme weather events in U.S. counties on the associated damage from the events. Our underlying hypothesis is that an increase in frequency will reduce damage because it will incentivize counties to invest in adaptation capital. We conduct our analysis separately for different categories of extreme weather events, since this adaptation likely varies with the type of extreme weather. For example, storm drains reduce the damage from both flash and coastal floods, but they have little effect on the damage from a tornado. Therefore, we analyze a "floods" category which includes both flash and coastal flood events and a separate "tornado" category.

We estimate the following equation for each weather category

$$\ln(normDamage_{it}) = \beta_0 + \beta_1 frequency_{it} + \beta_2 severity_{it} + \beta_3 type_{it} + \alpha_i + \gamma_y + \gamma_m + \varepsilon_{it}, \quad (1)$$

where subscript i denotes the county and subscript t denotes day. The dependent variable, *normDamage*, measures the monetary property damage from the event, normalized by county GDP. Following Hsiang and Narita (2012), we normalize damage by GDP because the damage is likely to be larger in more heavily developed and densely populated counties.

The data on normalized damage are positively skewed because there are many observations for which there is no report of a given type of extreme weather event. To address this skewness and any potential bias in the results from extreme outliers, we use a log transformation of the normalized damage (Bohra-Mishra, Oppenheimer, and Hsiang, 2014; Ebke and Combes, 2013; Loayza et. al, 2009).[6,7]

To measure the effect of event frequency on damage, it is essential to control for the severity of the event, since severity could be correlated with frequency and more severe events likely result in more damage. We include two measures of event severity. The first measure, *severity*, quantifies the magnitude or the duration of event, independent of the type of event in the weather category. The second measure, *type*, is a vector of indicator variables for each type of event in the category. These indicators allow the type of event to impact damage, all other variables, including *severity*, held constant. Returning to our flood category example, *severity* measures the duration of the flood while *type* includes indicator variables for flash and coastal floods.

Finally, variable $frequency$ measures how often a county experienced events in the weather category in recent years. We include county, α_i, year, γ_y, and month, γ_m, fixed effects. Thus, our identifying variation comes from within county changes over time. We hypothesize the following signs for the coefficients:

$$\beta_1 > 0, \quad \text{and} \quad \beta_2 < 0.$$

Coefficient $\beta_1 > 0$ implies that an increase in event severity will increase damage, holding both frequency and type constant; more severe events cause more damage. Coefficient $\beta_2 < 0$ implies that an increase in frequency reduces the damage associated with the event. Again, our hypothesized mechanism linking frequency and damage is adaptation; increases in frequency incentivize counties to invest in adaptation, which reduces damage from future events in the same weather category.

[6] Specifically, our dependent variable is $\max(\ln(y, 0.000000001))$ where y is monetary damage relative to GDP.

[7] Following Dougherty (2011), we compare the r-squared values in the regressions of the dependent variable and logged dependent variable normalized by their respective geometric means to evaluate the goodness of fit in the logged relative to non-logged specifications. We find that the log specification has a higher adjusted r-squared for every weather category that we include in our empirical analysis.

3 Data

Our data on extreme weather events are from the National Oceanic and Atmospheric Administration's National Climatic Data Center's (NCDC) storm events database. This database reports county-level information on 48 different types of extreme weather events from years 1950-2015. However, data is only available starting in 1996 for many types of extreme weather. These data include the type of event, the date and time of the event, the number of direct and indirect fatalities and injuries caused by the event, and the dollar values of the associated property and crop damage. Additionally, we also use data on county GDP from the Census Bureau's U.S.A. Counties Database and annual data on state GDP from the Bureau of Economic Analysis.

In Section 3.1, we construct our empirical measures of the severity, damage, and frequency. In Section 3.2, we discuss our selection criteria for which of the 48 types of weather events we include in our analysis and divide the included events into broad weather categories.

3.1 Measures of severity, damage, and frequency

The NCDC data record a direct measure of the magnitude for hail storms, wind events, and tornados, which we use for our measure of severity in equation (1). The respective magnitude measures for these three events are the diameter of the hail, the wind speed, and the F-scale (Enhanced Fujita Scale).[8] For all other types of weather events, we use the duration of the event in hours, to proxy for its severity. For example, a two-day blizzard is more severe than a blizzard that ends after a single day.

We use the dollar value of the associated property damage to measure the damage caused by each event. Property damage includes damage to public and private infrastructure, objects, and vegetation. Property damage estimates can come from insurance claims, estimates by qualified individuals, or estimates by the preparers of the NCDC data.

[8] The F-scale for tornados ranges from zero to five, with five being the most severe.

While the NCDC data also include information on crop damage, we focus our analysis exclusively on property damage. Data on crop damage are largely from insurance claims. The number of farmers with crop insurance has increased over time (because it has become more attractive or required by their banks), causing the reported crop damage to also increase. We exclude crop damage from our analysis to avoid these potential measurement errors.[9]

As discussed in Section 2, we normalize monetary damage by the county's GDP. However, county-level data on GDP are only available for the years 1969, 1979, 1989, 1999, and 2005-2009. Therefore, we interpolate county-level GDP within each decade from annual data on state-level GDP. We construct this interpolation so that the patterns of economic growth at the county level match the patterns at the state level. For example, if the state experienced rapid growth from 1970-1974, and then relatively stagnant growth from 1975-1979, we assume that each county within the state experienced the same rapid growth from 1970-1974 and stagnant growth from 1975-1979. Since extreme weather events likely impact a county's GDP, the ideal normalization would be to divide monetary damage by the GDP the county would have had in the absence of the extreme weather event. Our interpolation method provides an estimate of this counterfactual GDP, bringing us closer to the ideal.

We aggregate the event-level NCDC data to the daily level to put chronological structure on the data. A small fraction of county-day observations have events that span multiple days.[10] For these multi-day events, we allocate the event and all of its damage to the day on which the event began. Additionally, a small fraction of county-day observations have more than one incident of events in the same weather category on the same county-day.[11] For these observations, we aggregate our measures of damage and severity. Specifically, for hail storms, tornados, and wind events, we use the maximum magnitude observed in the day

[9]The NCDC data also included data on human fatalities and injuries. However, this data is sparsely reported for many types of extreme weather events.

[10]Specifically, in our final estimation sample, 5 percent of county-day observations with an event have an event that spans multiple days. The majority of these multi-day events are floods.

[11]Specifically, in our final estimation sample, 23 percent of county-days with an event have more than one incident of events in the same weather category. The majority of these multi-event observations are for hail; excluding hail, only 11 percent of county-days with an event have more than one incident of an event in the same weather category.

and the total damage. For example, a county-day observation of a tornado is the maximum F-scale of all tornados in that day and the total property damage from all tornados in that day. For all other types of weather events, we use the total duration from all the incidences of that weather event in the county-day and the total damage. For example, one county-day observation of a flood is the total duration (in hours) and total property damage of all floods in that county on that day.

We define the frequency of a weather category as the number of events within the category that occurred during one year. In our preferred specification, we use the average value of the annual frequency over a three year period which ends one year before the current observation. For example, our frequency measure for an observation on November 20, 2006 would be the average annual frequency of the weather category from November 20, 2002 through November 20, 2005.

We average our measure of frequency over three years to capture longer-term shifts, or perceived shifts, in the distribution of extreme weather. We lag the frequency measure by one year to allow time for the agents to make decisions based on changes in the frequency of extreme weather. Our results are generally robust to frequency definitions which average over one, two, four, five, or six years (instead of three) and to lag lengths ranging from zero months to four years (see Appendix Tables B.1-B.10).

3.2 Categories of extreme weather events

The NCDC data report 48 different types of extreme weather events, ranging from flash floods to dust storms. We divide these events into broad weather categories based on their general characteristics. For example, we include all flood-related events in one, "flood" category. Many of these weather categories do not have reasonable measures of severity or have too few observations with damage and severity measures to provide sufficient statistical power for our analysis. We require that all weather categories in our analysis have over 10,000 observations, at least 1,000 of which must have nonzero (and non-missing) damage estimates.

We include the following five categories of events in our analysis: floods, hail, tornados, wind, and winter weather.[12] The floods category includes coastal floods, flash floods, lakeshore floods, and other floods. The wind category includes high wind and strong wind events. The winter weather category includes blizzards, ice storms, lake-effect snow, sleet, and winter weather. Hail and tornados only include the single event.[13]

For floods, wind, and winter weather events, we restrict our analysis to years 1996-2009 because the NCDC data for these events start in 1996 and the county-level GDP data are only available through 2009. However, the NCDC data for hail and tornados are available from 1950 onwards and county-level GDP data are available from 1969 onwards, making the analysis over a much longer time period (1969-2009) feasible for these two weather categories. Due to computational difficulties, we are currently unable to extend the sample all the way back to 1969. Instead, we analyze tornado and hail events over the 1986-2009 time period. In ongoing work, we expand the analysis to cover the full range of available data for these two weather categories.

Table 1 reports the summary statistics for each weather category we include in our analysis. Hail is the most common category; the average number of hail events per year is more than double that of any other category. However, the distribution of annual hail events over counties has a long right tail; the 99th percentile of annual hail events in a county is over 18. This long right tail occurs because a small number of counties, located mainly in the plains of Kansas, Oklahoma, Texas, Colorado, and Nebraska, often experience many hail storms per year. At the upper end of this extreme, Sedgwick County, Kansas experienced 96 hail events in 2008, including fourteen days with more than one hail storm.

While tornados are the least frequent weather category in our sample, they are by far the

[12] One noteworthy event type that our severity criterion excludes from our analysis is hurricanes. While the NCDC data include hurricanes, the magnitude of the hurricane is recorded for less than 10 percent of the observations, making it infeasible to control for hurricane severity at the county level. Using global data sets, Bakkensen and Mendelsohn (forthcoming) and Hsiang and Narita (2012) find evidence of adaptation to hurricanes across countries.

[13] Appendix A.1 reports the NCDC's definitions of these events.

most damaging, with average property damage equal to 952,643 in 2010 dollars. Floods are the second most damaging weather category in our sample and the second most common. The maximum number of floods per year occurred in San Bernardino County, California in 2005 when the county experienced 63 flash floods, including fourteen days with more than one flash flood. However, over our sample, the 99th percentile of annual floods in a county is 8, making San Bernardino county in 2005 an outlier.

Table 1: Summary Statistics

	Flood	Hail	Tornado	Wind	Winter
Mean events per county per year	0.8	1.7	0.2	0.3	0.3
Median events per county per year	0	0	0	0	0
Max events per county per year	63	96	22	109	26
Mean property damage per event[1]	370,302	77,280	952,643	163,043	171,513
Mean severity[2]	28.2	1.2	0.7	51.0	17.2
Number of counties[3]	3,061	3,095	2,867	1,603	1,496
Average annual county GDP	6,510 million in 2010 dollars				

[1]Conditional upon experiencing an event. Measured in 2010 dollars.

[2]Duration (in hours) for floods and winter; magnitude for hail, wind, and tornados.

[3]Number of counties that experience at least one event from 1996-2009 (1986-2009 for hail and tornadoes).

4 Empirical results

Table 2 reports our main results from the estimation of equation (1) for floods, hail, tornados, wind, and winter. Coefficient estimate β_1 is negative for all weather categories and statistically significant for all categories except for hail and wind. The magnitudes of the estimates imply that if frequency increases by one event per year, damage relative to GDP falls by 0.1 percent for floods, 0.03 percent for tornados, and 0.1 percent for winter. These marginal reductions in damage correspond to decreases in the value of damage equal to 395, 112 and 233 in 2010 dollars, respectively.

We hypothesize that adaptation drives the negative relationship between frequency and damage. For example, counties can reduce flood damage by installing storm drains and reduce winter weather damage by investing in snow removal equipment. With regards to tornados, there are not many adaptation measures that can save a structure if a tornado passes directly through it. However, investments in wind-resistant materials and construction techniques can substantially reduce the damage to structures that are not directly hit. For example, the building codes in Moore Oklahoma (located in the tornado belt of the midwest) require garage doors that can withstand winds of up to 130 miles per hour as well as the use of "hurricane clips of framing anchors to tie the house together effectively [and] continuous wood structural panel sheathing on all exterior walls to strengthen the home."[14]

We do not find statistically significant effects of changes in frequency on the damage from hail or wind events. While individuals can adapt to hail with small behavioral changes, such as parking a car in the garage, we are not aware of any large scale measures that substantially reduce hail damage. Adaptation strategies for wind events are likely to be similar to those for tornados. However, the wind events are generally less severe than tornados; the mean wind speed is only 51 knots, while the mean tornado has magnitude 0.7, which implies wind speeds closer to 78 knots on average (Table 1).[15] One possible explanation for the insignificant wind results is that the tornado adaptation investments are only necessary to prevent damage at very high wind speeds; at lower wind speeds, the damage the adaptation investments are designed to prevent would not occur to begin with, even without adaptation.

[14]"Moore adopts new building codes; first city in nation to address tornado impact on homes" News Release, March 17-2014.

[15]Category 0 tornados have wind speeds ranging from 35-63 knots and category 1 tornados have wind speeds ranging from 63 to 97 knots.

Table 2: Estimation Results

	(1) Flood	(2) Hail	(3) Tornado	(4) Wind	(5) Winter
Frequency	-0.00107**	-7.33e-05	-0.000286**	-0.000780	-0.00136**
	(0.000424)	(0.000173)	(0.000130)	(0.000625)	(0.000520)
Duration	0.00528***				0.0130
	(0.00166)				(0.0126)
Magnitude		0.937***		0.0570***	
		(0.132)		(0.00931)	
Tornado F-0			3.541***		
			(0.343)		
Tornado F-1			9.319***		
			(0.396)		
Tornado F-2			12.01***		
			(0.414)		
Tornado F-3			14.28***		
			(0.251)		
Tornado F-4			15.79***		
			(0.408)		
Tornado F-5			17.04***		
			(0.689)		
Coast Flood	2.993***				
	(1.067)				
Flash Flood	2.557***				
	(0.208)				
Flood	2.506***				
	(0.272)				
Lake Flood	8.870***				
	(0.556)				
High Wind				-0.0430	
				(0.167)	
Strong Wind				4.494***	
				(0.521)	
Blizzard					1.213*
					(0.687)
Ice Storm					3.577***
					(0.586)
Lake Snow					3.039*
					(1.792)
Sleet					-0.215
					(0.192)
Winter Weather					0.606
					(0.449)
Constant	-20.72***	-20.73***	-20.72***	-20.72***	-20.72***
	(0.00186)	(0.00121)	(0.000281)	(0.000714)	(0.000763)
Year FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y
Observations	11,674,619	27,991,887	28,002,557	11,672,495	11,674,623
R^2	0.309	0.150	0.709	0.481	0.224

Robust standard errors in parentheses

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

Dependent variable is log of normalized property damage.

Frequency is 3-year rate with a 1-year lag.

Coefficient estimate β_2 is positive for all weather categories and statistically significant for all categories except winter, implying that more severe events cause greater damage, event type held constant. In the case of tornados, we include a dummy variable for each value of the F-scale, zero through five. As expected, tornados with higher values of the F-scale cause more damage. For the flood, wind, and winter categories, we include indicator variables for each specific type of extreme weather event, since certain types of events could cause more damage than other types. For example, our results indicate that lake floods result in greater damage than other types of floods.

Our empirical results reveal a negative and significant relationship between frequency and damage. While we interpret this finding as evidence that counties can adapt to extreme weather, an alternative explanation is that counties are slow to rebuild their infrastructure following an extreme weather event. Specifically, suppose that a recent event causes $frequency$ to increase. Suppose further that this event destroys a portion the county's infrastructure and that the infrastructure is not immediately rebuilt. Then, when a second event occurs, there is less infrastructure to destroy. For example, consider a tornado that levels some of the buildings in a particular county. If those buildings are not rebuilt right away and a future tornado takes the same path, then the damage from the second tornado will be smaller than the damage from the first tornado, all else constant.

If this "slow to rebuild" effect drives the results, then we would expect to see the magnitude of the negative relationship between frequency and damage decrease with longer lag times for our frequency measure. As the lag time between the frequency of previous events and the current event increase, relatively more of the infrastructure that was destroyed by previous events is rebuilt. Appendix Tables B.1-B.5 test the robustness of the results for frequency lag times equal to zero, six month, one year, two year, three year, and four years.[16] The magnitude of the of the coefficient on frequency, β_1, is reasonably similar across the different

[16]Note that the frequency measure for a zero year lag includes events that happened between zero and three years ago. While a county may not have had time to adapt to very recent events, it will have had time to adapt to events that happened three years ago. Therefore, we should expect to see some adaptation even with the zero year lag.

lag specifications. This near constancy suggests that the “slow to rebuild” effect is not responsible for the negative and significant relationship between frequency and damage, further supporting the hypothesis that counties adapt in response to extreme weather.

Finally, our main specification uses the annual $frequency$ averaged over a three year period. Averages over shorter time periods result in greater volatility since an outlier year receives more weight. Averages over longer periods reduce the sample size and hence the statistical power of our estimation.[17] Appendix Tables B.6-B.10 report the results for frequency averaged over one, two, three, four, five, and six year periods. The magnitude of the coefficient on frequency, β_1, is reasonably similar across these different specifications for all the weather categories.

5 Model

Our empirical results imply that a marginal increase in frequency reduces the damage the county experiences from future events for floods, tornados, and winter weather events. We hypothesize that adaptation drives this negative relationship. For a given weather category, increases in the frequency of events increase the perceived probability of future events, which raises the returns to adaptation investments. We develop a model to formalize these links between frequency, adaptation, and damage. We use the model to quantify the amount of adaptation across U.S. counties with different susceptibilities to extreme weather and its contribution to damage reduction.

We analyze an economy that periodically experiences extreme weather events such as tornados, floods and winter weather. These events cause damage, which lowers output. However, agents can invest in a special type of capital, called adaptation capital, to reduce their damage from extreme weather. Examples of adaptation capital include storm drains,

[17] Specifically, for the weather categories with data beginning in 1996, the three-year frequency average with a one year lag requires that we restrict our estimation to the sample from years 2000 onward. Similarly, a four-year frequency average with a one year lag requires that we restrict our estimation to the sample from years 2001 onward. Analogous reductions in sample size apply to the weather categories with data beginning in 1986.

sea walls, snow plows, wind-resistant garage doors, etc.

Our focus is not on the overall level of capital, but rather on its allocation between adaptation and its typical productive use. Therefore, we build off of the standard Solow framework and model an economy with a constant savings rate. Taking this savings rate as given, agents choose next period's proportion of adaptation capital to maximize the expected welfare, conditional on the probability distribution of extreme weather. The model time period is one year. For each weather category, we calibrate the model parameters from our empirical estimates of the effects of an increase in frequency on damage. We discuss each component of the model in turn.

5.1 Firms

Capital, K, can be used for production, K^P, or for adaptation, K^A. Let a be the fraction of total capital used for adaptation and $1-a$ be the fraction used for production. A unit mass of perfectly competitive firms combines the production capital with labor, L, to produce output, Y, according to the Cobb-Douglas production function

$$Y = A((1-a)K)^{\alpha} L^{1-\alpha}, \tag{2}$$

where parameters A and α denote total factor productivity and capital share, respectively.

5.2 Extreme weather

5.2.1 Damage

An extreme weather event causes damage, D, which depends on the proportion of adaptation capital and on output according to

$$D = h(a)\Omega Y. \tag{3}$$

Damage increases with output. For example, a tornado that hits a densely populated urban center will cause more damage than a tornado that passes through rural farmland. The function $h(a)$ models the effect of adaptation capital on damage. The function satisfies four properties

$$h'(a) < 0, \quad h''(a) > 0, \quad h(0) = 1, \quad \text{and} \quad h(1) = 0.$$

The negative first derivative, $h'(a) < 0$, requires that adaptation capital reduce the damage from extreme weather. The positive second derivative, $h''(a) > 0$, implies that there are diminishing returns to adaptation investments. For example, in the case of floods, agents might first install storm drains and then build a levee. Compared to a levee, the storm drains are relatively cheap and more effective per dollar spent.

The endpoint $h(0) = 1$ implies that with no adaptation, damage from the extreme weather event equals ΩY. Thus, constant $\Omega < 1$ is the fraction of output lost to extreme weather in the absence of adaptation. The endpoint $h(1) = 0$ implies that if all capital is used for adaptation, then there is no damage from extreme weather. However, in this case, output is zero because productive capital is an essential input in the Cobb-Douglas production function (equation (2)). The diminishing returns to productive and adaptive capital imply that it is never optimal to reach this extreme.

We use a simple functional form for $h(a)$ that satisfies these four assumptions,

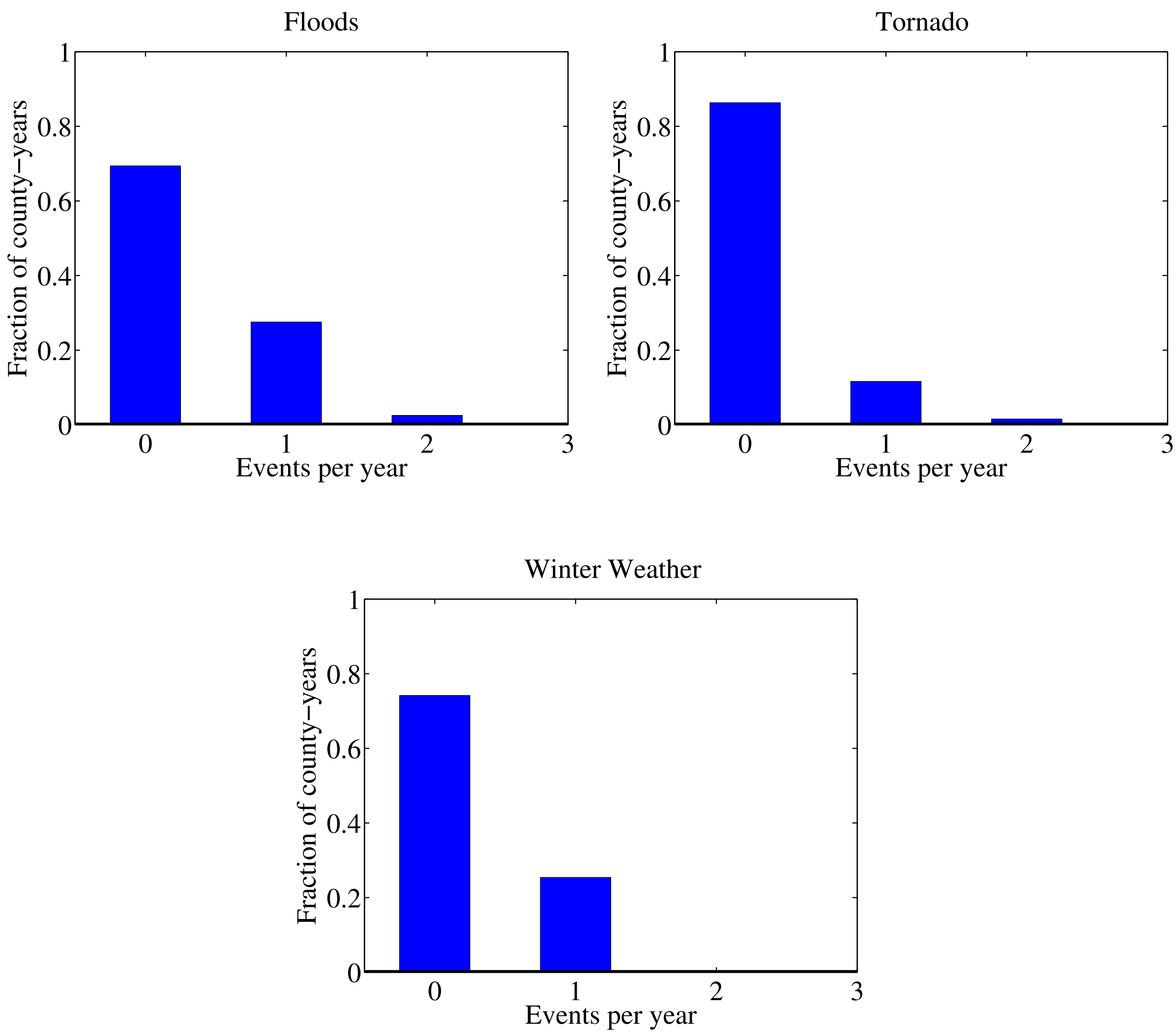
$$h(a) = 1 - a^{\theta}. \tag{4}$$

Curvature parameter θ governs the diminishing returns to the proportion of adaptation capital. If $\theta = 1$, then $h(a)$ is linear and the marginal return to adaptation is constant. Diminishing returns require $\theta < 1$; smaller values of θ create stronger diminishing returns.

5.2.2 Probability distribution of extreme weather events

Extreme weather events are stochastic. Figure 1 shows the annual distribution of extreme weather events for the subset of counties in our sample that experienced the median number of events, conditional on experiencing at least one event in the weather category. The x-axis is the number of events per year (within the weather category) and the y-axis is the fraction of county-years in our sample during which the median counties observed each value on the x-axis. The large mass at zero for each weather category implies that incidents of extreme weather are relatively rare.

Figure 1: Distribution of events per year for the median counties



We approximate the yearly distribution of extreme weather with two outcomes: (1) zero events from a given weather category occur during the year, (consistent with the large masses at zero in Figure 1), and (2) at least one event from the weather category occurs during the year. We use the daily frequency of events within a weather category, f, to model the probability of each of these outcomes. Unlike the annual frequency, the daily frequency is always less than unity. Therefore, we can interpret the daily frequency as the probability than an event will occur on any given day. It follows that the probability that at least one event will occur in a given year, $p(f)$, is one minus the probability that zero events occur,

$$p(f) = 1 - (1 - f)^{365}. \tag{5}$$

Zero events occur (outcome one) with probability $1 - p(f)$, and at least one event occurs (outcome two) with probability $p(f)$. However, the expected damage from the realization of outcome two depends critically on how many events occur, given that at least one event occurs. Define the conditional expected number of events, $\mu(f)$, as the expected number of events, conditional on the occurrence of at least one event. Bayes' Rule then implies that $\mu(f)$ equals

$$\mu(f) = \sum_{j=1}^{365} \left(\frac{\binom{365}{j} f^j (1 - f)^{365-j}}{p(f)} \right) j. \tag{6}$$

The term, $\frac{\binom{365}{j} f^j (1-f)^{365-j}}{p(f)}$, is the probability that j events occur in a year, conditional on the occurrence of at least one event, for $j = 1$ to 365. Multiplying these probabilities by the number of events, j, yields the conditional expected number of events, $\mu(f)$. Increases in the daily frequency of events increase the conditional expected number of events, $\mu'(f) > 0$; as the probability of an event each day rises, the conditional expected number of events in a year also rises.[18]

[18] In ongoing work, we develop a richer model of the probability distribution of extreme weather that includes more than the two outcomes in the current specification. Specifically, we model a discrete distribution

5.2.3 Net output

A single extreme weather event causes damage, $D = h(a)\Omega Y$. It follows that $\mu(f)$ extreme weather events cause damage, $\mu(f)D = \mu(f)h(a)\Omega Y$. Let $\tilde{Y}$ denote output net of damage from extreme weather. Define indicator variable $e = 1$ if $\mu(f)$ extreme weather events occur and $e = 0$ if there are no incidents of extreme weather. We have:

$$\tilde{Y}_t = \begin{cases} Y_t & : e = 0 \\ Y_t - \mu(f)D_t = Y_t(1 - \mu(f)h(a_t)\Omega) & : e = 1 \end{cases} \tag{7}$$

5.3 Households

Households save an exogenous fraction, $\bar{s}$, of their net income and consume the other fraction. Thus consumption, C, equals: $C_t = (1 - \bar{s})\tilde{Y}_t$. Preferences over consumption are logarithmic. Total capital accumulates according to the standard law of motion,

$$K_{t+1} = (1 - \delta)K_t + I_t = (1 - \delta)K_t + \bar{s}\tilde{Y}_t, \tag{8}$$

where δ is the depreciation rate and $I_t = \bar{s}\tilde{Y}_t$ is period t investment.

In period t, the agents must allocate capital in period $t + 1$ to production or adaptation. Thus, both the production and adaptation capital stocks are predetermined in each period. There are no adjustment costs; agents can costlessly turn period t adaptation capital into period $t + 1$ production capital and vice versa.

5.4 Optimization

We solve the agent's optimization problem to calculate the optimal proportion of adaptation capital. Taking the exogenous savings rate as given, the agent chooses the proportion

where p_0 is the probability of zero events, p_1 is the probability of one event, p_2 is the probability of two events, and so on.

of adaptation capital to maximize the present discounted value of lifetime utility

$$\max_{\{a_{t+1}\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \ln(C_t)$$

subject to equations (2) - (8). The expectation is taken with respect to the probability distribution for extreme weather events.

The first order condition with respect to a_{t+1} yields the standard optimality condition that the agent chooses the proportion of adaptation capital to equate the expected marginal benefits from adaptation with the marginal cost:

$$p(f)\left(\frac{\partial(1-\mu(f)h(a_{t+1})\Omega)}{\partial a_{t+1}}\right)Y_{t+1}\left(\frac{C_{t+1}|e=0}{C_{t+1}|e=1}\right) = -\frac{\partial Y_{t+1}}{\partial a_{t+1}} \tag{9}$$

The marginal benefits of adaptation capital (lefthand side of equation (9)) are the reduction in damage from extreme weather, $\left(\frac{\partial(1-\mu(f)h(a_{t+1})\Omega)}{\partial a_{t+1}}\right)Y_{t+1}$, multiplied by the probability of extreme weather, $p(f)$, and the marginal utility when extreme weather occurs relative to the marginal utility when no extreme weather occurs, $\left(\frac{C_{t+1}|e=0}{C_{t+1}|e=1}\right)$.

The marginal cost of adaptation capital (righthand side of equation (9)) is the forgone output from the lower levels of productive capital, $\frac{\partial Y_{t+1}}{\partial a_{t+1}}$. This cost does not depend on the probability of extreme weather events, since it realizes regardless of whether or not extreme weather occurs.[19]

Substituting the functional form assumption, $h(a) = 1 - a^{\theta}$, yields an expression which defines the optimal proportion of adaptation capital, $a^{\star}$:

$$\alpha = p(f)(1-a^{\star})\left(\frac{\mu(f)\theta(a^{\star})^{\theta-1}\Omega}{1-\mu(f)(1-(a^{\star})^{\theta})\Omega}\right) \tag{10}$$

Increases in the damage from extreme weather, Ω, increase the optimal proportion of adap-

[19]Note that when extreme weather occurs, the utility cost of the forgone output with adaptation is higher than without but but the absolute loss in (net) output is smaller with adaptation than without. Logarithmic preferences imply that these two effects perfectly cancel.

tation capital, $\frac{\partial a^\star}{\partial \Omega} > 0$. Increases in the importance of capital in the production process decrease the optimal proportion of adaptation capital, $\frac{\partial a^\star}{\partial \alpha} < 0$. Finally, an increase in the daily frequency of events increases the optimal proportion of adaptation capital. We have

$$\frac{\partial a^\star}{\partial f} = \frac{p'(f)\theta\left[(a^\star)^{\theta-1} - (a^\star)^{\theta}\right] + \left(\frac{\alpha}{\Omega}\right)\left(\frac{1}{\mu(f)}\right)^2 \mu'(f)}{(1-\theta)\theta p(f)(a^\star)^{\theta-2} + \theta(a^\star)^{\theta-1}(p(f)\theta+\alpha)} > 0. \tag{11}$$

5.5 Calibration

Table 3: Parameter Values

Parameter	Flood	Tornado	Winter
Capitial share: α	0.36	0.36	0.36
Damage constant: Ω	4.82e-04	2.59e-03	9.68e-04
Curvature parameter: θ	0.48	0.62	0.50
Daily event frequency: f	4.19e-03	1.07e-03	1.41e-03
Standard deviation of f: σ	7.55e-03	2.67e-03	4.29e-03
Maximum of f: $\max(f)$	0.22	0.08	0.11
Annual event probability: $p(f)$	0.78	0.32	0.40
Cond. expected number of events: $\mu(f)$	1.95	1.21	1.28

We calibrate the model for the three weather categories for which we find a statistically significant relationship between frequency and damage: floods, tornados, and winter weather. We use the calibrated model to quantify the proportion of adaptation capital and its effects on damage from events in each of these weather categories. The model has four parameters to be determined: $\{\alpha, f, \theta, \Omega\}$. For all weather categories, we set capital share, α, equal to 0.36, its standard value in the U.S. data. The remaining three parameters vary with the category of extreme weather.

We choose the daily frequency of events, f, equal to its average value in our sample for each weather category (fourth row of Table 3).[20] From the daily frequency of events, we can calculate the probability of having at least one event in a given year, $p(f)$, and the conditional expected number of events, $\mu(f)$. The last two rows of Table 3 report these values for each weather category. Consistent with the summary statistics in Table 1, tornado is the rarest category in our sample, with annual probability equal to 0.32, while flood is the most frequent category in the sample, with annual probability equal to 0.78. The conditional expected number of events is between one and two events per year for all three weather categories.

Parameter Ω represents the fraction of output lost to extreme weather when adaptation capital equals zero. To calibrate Ω, we use the estimated coefficients from our empirical model (Table 2) to predict the average value of damage when the regressor $frequency$ equals zero. Zero adaptation capital is only optimal if the probability of events in the weather category is zero, which implies that the annual frequency of events is also zero. The second row of Table 3 reports our predicted value of Ω for each weather category.

Finally, we calibrate the curvature parameter, θ, for each weather category from our empirical estimate of $\hat{\beta}_1$ in Table 2. Coefficient estimate $\hat{\beta}_1$ is the partial derivative of the log of damage relative to GDP with respect to an increase in the frequency of the particular weather category. Using the notation from the model, this estimate corresponds to

$$\hat{\beta}_1 = \left(\frac{\partial h(a)\Omega}{\partial f}\right)\left(\frac{1}{h(a)\Omega}\right). \tag{12}$$

Rearranging equation (12) and applying the chain rule to the derivative yields

$$h(a)\Omega\hat{\beta}_1 = \left(\frac{\partial h(a)\Omega}{\partial f}\right) = \left(\frac{\partial h(a)\Omega}{\partial a}\right)\left(\frac{\partial a}{\partial f}\right). \tag{13}$$

Equation (13), together with the optimal proportion of adaptation capital, equation (9),

[20] We use a rolling 365 day window to calculate the daily frequency of events for each observation in our sample. Specifically, for an observation on day t the daily frequency of events is the total number of events (within the weather category) between days t and $t - 365$ divided by 365.

form a system of two equations with two unknowns, θ and $a^\star$.[21] Solving this system for each weather category yields the curvature parameter, θ, and our estimate of the average proportion of adaptation capital, $a^\star$, across U.S. counties. The third row in Table 3 reports the value of the curvature parameter. For all weather categories, θ is considerably smaller than unity, implying substantial diminishing returns to the proportion of adaptation capital.

6 Model results: quantifying adaptation

We use our calibrated model to quantify the proportion of adaptation capital for each category of extreme weather and its effects on damage for counties with different susceptibilities to extreme weather. Within our framework, the daily frequency, f, determines the expected number of events the county experiences each year. Therefore, we characterize a county as more prone to a particular weather category if it has a higher daily frequency of events. We quantify the level of adaptation and its effect on damage for counties with daily frequency equal the sample average, one and two standard deviations above the average, and the maximum value in our sample.[22] The fifth and sixth rows in Table 3 report summary statistics with regards to the daily frequency.

Table 4 reports the proportion of adaptation capital for each weather category and daily frequency value. Referring to the first row of Table 4, the proportion of adaptation capital for counties with the average daily frequency is very small, ranging from 4.86e-8 in the case of tornados to 1.74e-6 in the case of floods. The total value of U.S. capital stock in 2014 is approximately 51.2 trillion in 2011 dollars.[23] Thus, if every U.S. county experienced extreme weather with the average daily frequency, the total value of adaptation capital in the U.S. would be less then 100 million dollars for each weather category.

[21] When we solve the system of equations, we multiply our empirical estimate of $\hat{\beta}_1$ by 365 because the empirical specification uses the annual frequency of events while our model specification uses the daily frequency of events.

[22] Parameter f is the only parameter that is different in more event-prone counties. Parameters α, μ, and Ω are the same as their values in Table 3.

[23] Capital data are from the Federal Reserve Bank of St. Louis Economic Data: fred.stlouisfed.org.

Table 4: Proportion of Adaptation Capital

	Flood	Tornado	Winter
Mean frequency: $f = \bar{f}$	1.74e-06	4.86e-08	4.86e-07
1 std. dev. above mean: $f = \bar{f} + \sigma$	1.25e-05	1.35e-06	7.91e-06
2 std. dev. above mean: $f = \bar{f} + 2\sigma$	3.25e-05	5.69e-06	2.43e-05
Max frequency: $f = \max(f)$	2.50e-04	4.85e-03	3.27e-03

While adaptation capital is small for the counties with the average daily frequency, areas that are more prone to extreme weather have larger concentrations of adaptation capital; the values in Table 4 increase substantially when the daily frequency rises. For example, comparing the first and second rows of Table 4, the proportion of adaptation capital increases by one order of magnitude for each weather category when daily frequency increases by one standard deviation from the mean. Figure C.1 in the Appendix plots the distribution of county-day observations with respect to the daily frequency for each weather category. The percent of county-day observations with daily frequency more than one standard deviation above the mean ranges from 3.5 percent for tornados to 9 percent for floods. The percent of county-day observations with daily frequency more than two standard deviations above the mean ranges from 1.6 percent for tornados to 3 percent for winter weather.

We find the highest proportion of adaptation capital, almost one half of one percent, in the tornado category with daily frequency equal to its observed maximum. This observation corresponds to Republic county Kansas, which experienced 28 tornados between June 2003 and June 2004. While the maximum daily frequency for tornados is relatively small in comparison to the other weather categories, damage from a tornado in the absence of adaptation is considerably larger then the other categories, creating stronger incentives for adaptation investments at each daily frequency value.

We consider three measures of the total effects of adaptation capital. Our first measure,

M_1, is the percent that adaptation reduces the damage from the event,

$$M_1 = (h(a) - 1) \times 100. \tag{14}$$

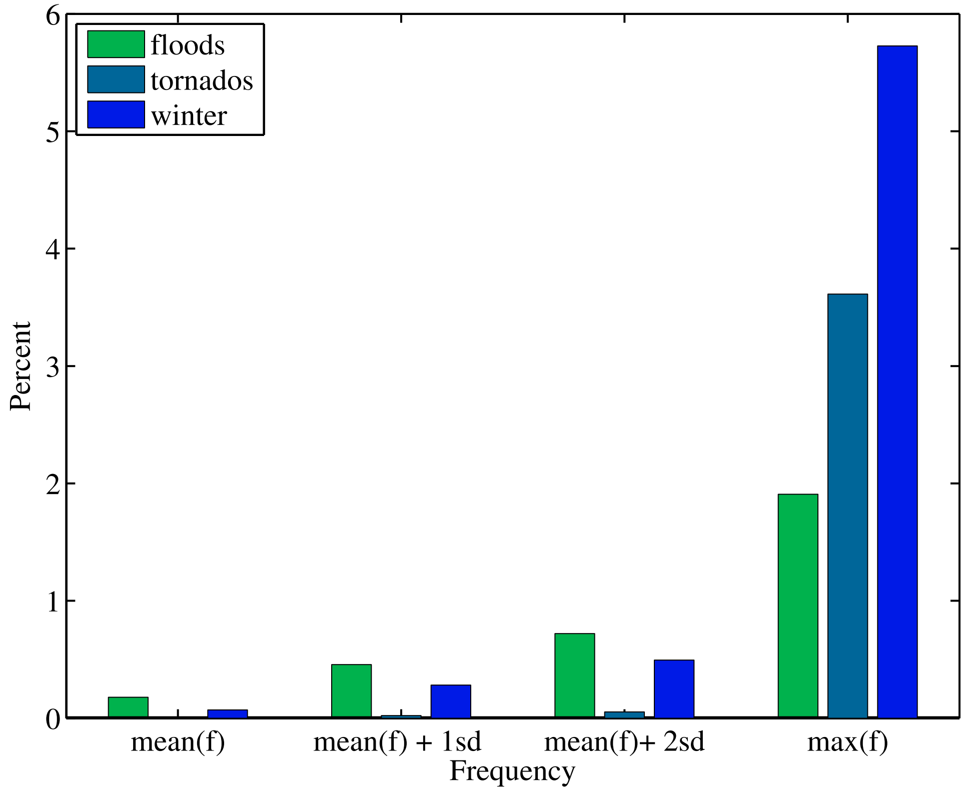
Figure 2 plots this effectiveness measure for each weather category and daily frequency value. Focusing first on the effects in regions with moderate values of frequency (less than or equal to two standard deviations above the mean), we see that adaptation reduces the damage from extreme weather by less than one percent (first three bins in Figure 2). Comparing across the three weather categories, we see the biggest reductions in damage from flood adaptation. Consistent with this result, floods have the smallest value of the curvature parameter, θ, and also the largest proportions of adaptation capital (Table 4) for daily frequencies below the observed maximum.[24]

The fourth bin in Figure 2 shows the reduction in damage for the maximum daily frequency in our sample, providing an upper bound on the amount that adaptation reduces the damage from each weather category. Here, we see the largest effects for tornados and winter weather, with maximum reduction in damage equal to 3.6 and 5.7 percent respectively. Consistent with these results, the proportion of adaptation capital is considerably higher for tornados and winter weather when $f = \max(f)$ then for floods (bottom row of Table 4).[25]

[24]Smaller values of θ correspond to larger reductions in damage for a given proportion of adaptation capital, a, because $a < 1$.

[25]Note that the curvature parameter, θ is larger for tornados and winter weather than for floods, dampening the effects of the larger adaption investments.

Figure 2: Percent Reduction in Damage From Adaptation (M_1)



Our second and third measures of the total effects of adaptation focus on its effects on output. Our second measure, M_2, is the percent that adaptation capital increases output in the event of extreme weather,

$$M_2 = \left(\frac{(1 - h(a)\mu(f)\Omega)(1 - a)^{\alpha}}{1 - \mu(f)\Omega} - 1 \right) \times 100. \tag{15}$$

Our third measure, M_3, is the percent that adaptation capital increases expected net output,

$$M_3 = \left(p(f) \left(\frac{(1 - h(a)\mu(f)\Omega)(1 - a)^{\alpha}}{1 - \mu(f)\Omega} \right) + (1 - p(f))(1 - a)^{\alpha} - 1 \right) \times 100. \tag{16}$$

The first section of Table 5 reports M_2 by weather category and daily frequency value and the second section reports M_3. Looking across weather categories and daily frequency values, we see the same patters for M_2 and M_3, that we did with the damage-only measure,

M_1. Specifically, adaptation has larger effects on conditional and expected net output when extreme weather events are more frequent. For moderate values of the daily frequency, flood adaptation has the largest effects on conditional and expected net output, while for the maximum value of frequency, tornado and winter adaptation have the largest effects.

Comparing the results in Table 5 with Figure 2, we see that magnitudes of the effects of adaptation on conditional and expected net output (M_2 and M_3) are smaller than its contribution to damage reduction alone (M_1). For example, when daily frequency equals its mean, $f = \bar{f}$, adaptation reduces the damage from floods by 0.18 percent but only reduces conditional and expected net output by 0.000105 and 0.0000687 percent, respectively. The smaller magnitudes for M_2 and M_3 occur because M_2 and M_3 include opportunity cost of devoting capital to adaptation instead of to production. Specifically, increases in the proportion of adaptation capital reduce the proportion of production capital, lowering output.

Comparing measures M_2 and M_3, we see that for all values of the daily frequency, the effects of adaptation on conditional net output are larger than its effects on expected net output. This difference occurs because the expected net output measure includes the probability that there are no incidents of extreme weather, in which case output is lower with adaptation capital than without. The difference between measures M_2 and M_3 decreases as the frequency increases and the two measures are almost identical when frequency equals its maximum value in the sample. This convergence occurs because as frequency increases, the annual probability of extreme weather approaches unity, which causes the value of expected net output to approach conditional net output.

Table 5: Effectiveness of Adaptation (Measures M_2 and M_3)

	Flood	Tornado	Winter
Percent change in net output conditonal on extreme weather (M_2)			
Mean frequency: $f = \bar{f}$	1.05e-04	6.94e-06	6.93e-05
1 std. dev. above mean: $f = \bar{f} + \sigma$	5.07e-04	5.62e-05	3.66e-04
2 std. dev. above mean: $f = \bar{f} + 2\sigma$	1.28e-03	1.59e-04	9.23e-04
Max frequency: $f = \max(f)$	9.86e-03	1.07e-01	1.19e-01
Percent change in expected net output (M_3)			
Mean frequency: $f = \bar{f}$	6.87e-05	1.05e-06	1.75e-05
1 std. dev. above mean: $f = \bar{f} + \sigma$	4.94e-04	2.94e-05	2.85e-04
2 std. dev. above mean: $f = \bar{f} + 2\sigma$	1.28e-03	1.24e-04	8.77e-04
Max frequency: $f = \max(f)$	9.86e-03	1.07e-01	1.19e-01

7 Conclusion

The steady accumulation of atmospheric carbon makes understanding our ability to adapt to climate change increasingly important. Yet, the analysis of adaptation is inherently difficult because we do not observe existing levels of adaptation capital. This lack of data makes it harder to learn from the past and quantify the steps areas have already taken to reduce the damage from extreme weather. This paper aims to partially fill this gap by estimating the empirical relationship between the frequency of extreme weather events and their associated damage and then using these estimates to calibrate a simple dynamic model of adaptation investment. We find a negative and statistically significant relationship between frequency and damage for floods, tornado, and winter weather events. However, when we use these estimates to discipline our model parameters, we find that the magnitude of the adaptation capital is very small. These small investments reduce the damage from extreme weather by less than one percent for the average county and by less then ten percent for the counties in the most event-prone areas.

The low existing levels of adaptation capital and its small effects on damage suggest that the cost of substantial adaptation investment outweighs the expected gains, even for counties that face a very high frequency of events. In some sense, this conclusion is rather pessimistic; counties in the most event-prone regions are unable or unwilling to take steps to reduce their damage from extreme weather. For example, Republic county, Kansas experienced 28 tornados in between June 2003 and June 2004, while Luce county, Michigan did not experience a single tornado between 1986-2009. Yet, our model results suggest that Republic county chose to allocate less than one half of one percent of its capital to adaptation, reducing its damage from tornados by less than five percent. This finding implies that if Luce county started to experience tornados, perhaps as a result of the changing weather patterns associated with climate change, there is little Luce county would choose to do to reduce the associated damage.

References

Agrawala, Shardu, Francesco Bosello, Kelly de Bruin, Carlo Carraro, Enrica de Cian, Elisa Lanzi (2010), "Plan or React?: Analysis of Adaptation Costs and Benefits Using Integrated Assessment Models," *OECD Environment Working Papers* No. 23, OECD publishing.

Agrawala, Shardu, Francesco Bosello, Carlo Carraro, Enrica de Cian, Elisa Lanzi, Mikael Skou Andersen, and Morten Soes Hansen (2011), "Adapting to climate change: costs, benefits, and modeling approaches," *International Review of Environmental and Resource Economics* 5(3), 245-284.

Bakkensen, Laura and Mendelsohn, Robert. (forthcoming), "Risk and adaptation: Evidence from global hurricane damages and fatalities," *Journal of the Association of Environmental and Resource Economists*.

Barrage, Lint (2015), "Climate change adaptation vs. mitigation: A fiscal perspective," edited by Bob Litterman. Wiley and Sons, forthcoming.

Bohra-Mishra, Pratikshya, Michael Oppenheimer, and Solomon M. Hsiang (2014), "Nonlinear permanent migration response to climate variations but minimal response to disasters," *Proceedings of the National Academy of Sciences* 27(111), 9780-9785.

Burke, Marshall, and Solomon M. Hsiang, and Edward Miguel (2015), "Global non-linear effect of temperature on economic production," *Nature*, 527, 235-239.

De Bruin, Kelly C., Rob B. Dellink, and Richard SJ Tol (2009), "AD-DICE: an implementation of adaptation in the DICE model," *Climatic Change*, 95(1-2): 63-81.

Dell, Melissa, Benjamin, Jones, and Benjamin Olken (2012), "Temperature shocks and economic growth: Evidence from the last half century," *American Economic Journal: Macroeconomics*, 4(3): 66-95.

Deschenes, Olivier, and Michael Greenstone (2011), "Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US," *American Economic Journal: Applied Economics*, (3): 152-185.

Dougherty, C., *Introduction to Econometrics*, fourth edition, Oxford University Press, 2011, Section 4.2.

Ebke, Christian and Jean-Louis Combes (2013), "Do remittances dampen the effect of natural disasters on output growth and volatility in developing countries?" *Applied Economics*, 45(16):2241-2254.

Felgenhauer, Tyler, and Mort Webster (2013), "Modeling adaptation as a flow and stock decision with mitigation," *Climate Change*.

Hornbeck, Richard (2012), "The enduring impact of the American Dust Bowl: Short- and long-run adjustments to environmental catastrophe," *American Economic Review*, 102(4): 1477-1507.

Hsiang, Solomon M., and Daiju Narita (2012), "Adaptation to cyclone risk: Evidence from the global cross-section," *Climate Change Economics*, 3(2).

IPCC (Intergovernmental Panel on Climate Change) eds. Nebojsa Nakicenovi and Rob Swart (2000), "Special report on emissions scenarios," Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

IPCC (Intergovernmental Panel on Climate Change) eds.Pachauri, Rajendra K., M. R. Allen, V. R. Barros, J. Broome, W. Cramer, R. Christ, J. A. Church et al.,"Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change" (2014): 151.

Loayza, Norman, Eduardo Olaberria, Jamele Rigolini, and Luc Christiansen (2009), "Natural disasters and growth- Going beyond the averages" *The World Bank Policy Research Working Paper Series No. 4980.*

Schlenker, Wolfram, and Michael J. Roberts (2009), "Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change," *Proceedings of the National Academy of Sciences*, 106(37): 15594-98.

Tol, Richard SJ. (2007), "The double trade-off between adaptation and mitigation for sea level rise: an application of FUND," *Mitigation and Adaptation Strategies for Global Change*, 741-753.

A Extreme weather event definitions

The following definitions come from the National Oceanic and Atmospheric Administration's National Climatic Data Center's (NCDC) documentation.[26]

Blizzard: A winter storm which produces the following conditions for 3 hours or longer: (1) sustained winds or frequent gusts 30 knots (35 mph) or greater, and (2) falling and/or blowing snow reducing visibility frequently to less than 1/4 mile, on a widespread or localized basis.

Coastal flood: Flooding of coastal areas due to the vertical rise above normal water level caused by strong, persistent onshore wind, high astronomical tide, and/or low atmospheric pressure, resulting in damage, erosion, flooding, fatalities, or injuries. Coastal areas are defined as those portions of coastal land zones (coastal county/parish) adjacent to the waters and bays of the oceans. Farther inland, the storm data preparer must determine when and where to encode a flood event as Flash Flood or Flood. Terrain (elevation) features will determine how far inland the coastal flooding extends.

Flash flood: A rapid and extreme flow of high water into a normally dry area, or a rapid water level rise in a stream or creek above a predetermined flood level, beginning within six hours of the causative event (e.g., intense rainfall, dam failure, ice jam-related), on a widespread or localized basis. Ongoing flooding can intensify to flash flooding in cases where intense rainfall results in a rapid surge of rising flood waters. The Storm Data preparer must use good, professional judgment in determining when the event is no longer characteristic of a flash flood and becomes a flood. Flash floods do not exist for two or three consecutive days.

Flood: Any high flow, overflow, or inundation by water which causes or threatens damage. In general, this would mean the inundation of a normally dry area caused by an increased water level in an established watercourse, or ponding of water, generally occurring more than 6 hours after the causative event, and posing a threat to life or property. This

[26] Available at http://www.nws.noaa.gov/directives/.

can be on a widespread or localized basis.

Hail: Frozen precipitation in the form of balls or irregular lumps of ice. Hail 3/4 of an inch or larger in diameter will be entered. Hail accumulations of smaller size which cause property and/or crop damage, or casualties, should be entered. Maximum hail size will be encoded for all hail reports entered.

High wind: Sustained non-convective winds of 35 knots (40 mph) or greater lasting for 1 hour or longer or winds (sustained or gusts) of 50 knots (58 mph) for any duration (or otherwise locally/regionally defined), on a widespread or localized basis. In some mountainous areas, the above numerical values are 43 knots (50 mph) and 65 knots (75 mph), respectively.

Ice storm: Ice accretion meeting or exceeding locally/regionally defined warning criteria (typical value is 1/4 or 1/2 inch or more), on a widespread or localized basis. The storm data preparer should include the times that ice accretion began, met criteria, and accretion ended.

Lakeshore flood: Flooding of lakeshore areas due to the vertical rise of water above normal level caused by strong, persistent onshore wind and/or low atmospheric pressure, resulting in damage, erosion, flooding, fatalities, or injuries. Lakeshore areas are defined as those portions of land zones (coastal county/parish) adjacent to the waters of the Great Lakes, Lake Okeechobee, Lake Pontchartrain and Lake Maurepas. Farther inland, the storm data preparer must determine when and where to encode a flood event as flash flood or flood. Terrain (elevation) features will determine how far inland the lakeshore flooding extends.

Lake-effect snow: Localized, convective snow bands that occur in the lee of large bodies of water, e.g. the Great Lakes or the Great Salt Lake, when relatively cold air flows over warm water. In extreme cases, snowfall rates of several inches per hour and thunder and lightning may occur. Lake-effect snow accumulations must meet or exceed locally defined 12 and/or 24 hour warning criteria (typical values of 6 to 8 inches within 12 hours or 8 to 10 inches within 24 hours). In some lake-effect snow events, structural damage, due to the excessive weight of snow accumulations, may occur in the few days following the meteorological end of the event. The storm data preparer should include this damage as part of the original event and give details in the narrative.

Sleet: Sleet accumulations meeting or exceeding locally/regionally defined warning criteria (typical value is 1/2 inch or more). The storm data preparer should include in the narrative the times that sleet accumulation began, met criteria, and ended.

Strong wind: Non-convective winds gusting less than 50 knots (58 mph), or sustained winds less than 35 knots (40 mph), resulting in a fatality, injury, or damage. Consistent with regional guidelines, mountain states may have higher criteria. A peak wind gust (estimated or measured) or maximum sustained wind will be entered.

Tornado: A violently rotating column of air, extending to or from a cumuliform cloud or underneath a cumuliform cloud, to the ground, and often (but not always) visible as a condensation funnel. Literally, in order for a vortex to be classified as a tornado, it must be in contact with the ground and extend to/from the cloud base, and there should be some semblance of ground-based visual effects such as dust/dirt rotational markings/swirls, or structural or vegetative damage or disturbance. EF-Scale values will be assigned to every documented tornado.

Winter weather: A winter precipitation event that causes a death, injury, or a significant impact to commerce or transportation but does not meet locally/regionally defined warning criteria. A winter weather event could result from one or more winter precipitation types (snow, or blowing/drifting snow, or freezing rain/drizzle), on a widespread or localized basis.

B Robustness tables

B.1 Different lag lengths for frequency

Tables B.1 - B.5 report the results for different lag-lengths for our measure of frequency. The coefficient estimates are reasonably stable across the specifications.

Table B.1: Flood Results, Different Frequency Lags

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Frequency (0yr lag)	-0.00114***						
	(0.000336)						
Frequency (6mo lag)		-0.00111***					
		(0.000395)					
Frequency (1yr lag)			-0.00107**				
			(0.000424)				
Frequency (18mo lag)				-0.000860*			
				(0.000499)			
Frequency (2yr lag)					-0.000954*		
					(0.000501)		
Frequency (3yr lag)						-0.000160	
						(0.000409)	
Frequency (4yr lag)							0.000132
							(0.000454)
Duration	0.00528***	0.00528***	0.00528***	0.00525***	0.00514***	0.00506***	0.00532***
	(0.00166)	(0.00166)	(0.00166)	(0.00168)	(0.00166)	(0.00158)	(0.00170)
Coast Flood	2.993***	2.993***	2.993***	2.991***	3.005***	3.002***	3.007***
	(1.067)	(1.067)	(1.067)	(1.067)	(1.072)	(1.072)	(1.081)
Flash Flood	2.558***	2.557***	2.557***	2.531***	2.491***	2.465***	2.485***
	(0.208)	(0.208)	(0.208)	(0.206)	(0.209)	(0.211)	(0.225)
Flood	2.507***	2.506***	2.506***	2.534***	2.567***	2.626***	2.707***
	(0.272)	(0.272)	(0.272)	(0.272)	(0.278)	(0.273)	(0.299)
Lake Flood	8.872***	8.871***	8.870***	8.876***	8.898***	8.917***	8.866***
	(0.556)	(0.556)	(0.556)	(0.559)	(0.560)	(0.556)	(0.564)
Constant	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***
	(0.00154)	(0.00161)	(0.00186)	(0.00233)	(0.00174)	(0.00209)	(0.00211)
Year FE	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y
Observations	12,836,968	12,260,918	11,674,619	11,092,947	10,504,884	9,338,344	8,171,804
R^2	0.309	0.309	0.309	0.309	0.308	0.311	0.320

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Dependent variable is log of normalized property damage.
Frequency is 3-year rate with specified lag.

Table B.2: Hail Results, Different Frequency Lags

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Frequency (0yr lag)	-6.31e-05						
	(0.000173)						
Frequency (6mo lag)		-9.10e-05					
		(0.000168)					
Frequency (1yr lag)			-7.33e-05				
			(0.000173)				
Frequency (18mo lag)				-3.17e-05			
				(0.000187)			
Frequency (2yr lag)					-4.00e-05		
					(0.000203)		
Frequency (3yr lag)						-1.31e-05	
						(0.000223)	
Frequency (4yr lag)							-5.33e-06
							(0.000237)
Magnitude	0.937***	0.937***	0.937***	0.937***	0.937***	0.937***	0.961***
	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)	(0.135)
Constant	-20.73***	-20.73***	-20.73***	-20.73***	-20.73***	-20.73***	-20.72***
	(0.00123)	(0.00122)	(0.00121)	(0.00122)	(0.00121)	(0.00120)	(0.000818)
Year FE	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y
Observations	27,991,887	27,991,887	27,991,887	27,991,887	27,991,887	27,991,887	26,833,191
R^2	0.150	0.150	0.150	0.150	0.150	0.150	0.154

Robust standard errors in parentheses

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

Dependent variable is log of normalized property damage.

Frequency is 3-year rate with specified lag.

Table B.3: Tornado Results, Different Frequency Lags

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Frequency (0yr lag)	-0.000445***						
	(0.000152)						
Frequency (6mo lag)		-0.000223*					
		(0.000124)					
Frequency (1yr lag)			-0.000286**				
			(0.000130)				
Frequency (18mo lag)				-0.000337**			
				(0.000160)			
Frequency (2yr lag)					-0.000273*		
					(0.000154)		
Frequency (3yr lag)						-0.000238***	
						(8.73e-05)	
Frequency (4yr lag)							-0.000283**
							(0.000108)
Tornado F-0	3.541***	3.541***	3.541***	3.541***	3.541***	3.541***	3.552***
	(0.343)	(0.343)	(0.343)	(0.343)	(0.343)	(0.343)	(0.341)
Tornado F-1	9.319***	9.319***	9.319***	9.319***	9.319***	9.319***	9.259***
	(0.396)	(0.396)	(0.396)	(0.396)	(0.396)	(0.396)	(0.395)
Tornado F-2	12.01***	12.01***	12.01***	12.01***	12.01***	12.01***	11.87***
	(0.413)	(0.414)	(0.414)	(0.414)	(0.414)	(0.414)	(0.423)
Tornado F-3	14.28***	14.28***	14.28***	14.28***	14.28***	14.28***	14.19***
	(0.251)	(0.251)	(0.251)	(0.251)	(0.251)	(0.251)	(0.262)
Tornado F-4	15.79***	15.79***	15.79***	15.79***	15.79***	15.79***	15.71***
	(0.408)	(0.408)	(0.408)	(0.408)	(0.408)	(0.408)	(0.390)
Tornado F-5	17.04***	17.04***	17.04***	17.04***	17.04***	17.04***	17.04***
	(0.689)	(0.689)	(0.689)	(0.689)	(0.689)	(0.689)	(0.689)
Constant	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***
	(0.000278)	(0.000275)	(0.000281)	(0.000290)	(0.000290)	(0.000281)	(0.000708)
Year FE	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y
Observations	28,002,557	28,002,557	28,002,557	28,002,557	28,002,557	28,002,557	26,843,498
R^2	0.709	0.709	0.709	0.709	0.709	0.709	0.702

Robust standard errors in parentheses

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

Dependent variable is log of normalized property damage.

Frequency is 3-year rate with specified lag.

Table B.4: Wind Results, Different Frequency Lags

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Frequency (0yr lag)	-0.00185***						
	(0.000524)						
Frequency (6mo lag)		-0.00138**					
		(0.000577)					
Frequency (1yr lag)			-0.000780				
			(0.000625)				
Frequency (18mo lag)				-0.000270			
				(0.000602)			
Frequency (2yr lag)					0.000269		
					(0.000545)		
Frequency (3yr lag)						0.000632	
						(0.000565)	
Frequency (4yr lag)							0.000900
							(0.000538)
Magnitude	0.0570***	0.0570***	0.0570***	0.0590***	0.0604***	0.0625***	0.0675***
	(0.00931)	(0.00931)	(0.00931)	(0.00954)	(0.00981)	(0.0102)	(0.0102)
High Wind	-0.0421	-0.0430	-0.0430	-0.0739	-0.0892	-0.0842	-0.156
	(0.167)	(0.167)	(0.167)	(0.170)	(0.170)	(0.179)	(0.197)
Strong Wind	4.496***	4.495***	4.494***	4.418***	4.371***	4.288***	4.096***
	(0.521)	(0.521)	(0.521)	(0.523)	(0.529)	(0.537)	(0.536)
Constant	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***
	(0.000539)	(0.000629)	(0.000714)	(0.000789)	(0.000754)	(0.000830)	(0.000894)
Year FE	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y
Observations	12,836,172	12,259,332	11,672,495	11,091,255	10,503,470	9,337,622	8,171,792
R^2	0.481	0.481	0.481	0.491	0.497	0.512	0.530

Robust standard errors in parentheses

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

Dependent variable is log of normalized property damage.

Frequency is 3-year rate with specified lag.

Table B.5: Winter Weather Results, Different Frequency Lags

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Frequency (0yr lag)	-0.00110**						
	(0.000423)						
Frequency (6mo lag)		-0.00131***					
		(0.000488)					
Frequency (1yr lag)			-0.00136**				
			(0.000520)				
Frequency (18mo lag)				-0.00122**			
				(0.000569)			
Frequency (2yr lag)					-0.00117***		
					(0.000386)		
Frequency (3yr lag)						-0.000193	
						(0.000274)	
Frequency (4yr lag)							0.000596
							(0.000599)
Duration	0.0130	0.0130	0.0130	0.00976	0.0130	0.0127	0.0121
	(0.0126)	(0.0126)	(0.0126)	(0.0116)	(0.0113)	(0.0110)	(0.0102)
Blizzard	1.213*	1.213*	1.213*	1.301*	1.132**	1.157**	1.142**
	(0.687)	(0.687)	(0.687)	(0.687)	(0.528)	(0.507)	(0.473)
Ice Storm	3.578***	3.577***	3.577***	3.476***	3.555***	3.777***	3.757***
	(0.586)	(0.586)	(0.586)	(0.575)	(0.599)	(0.602)	(0.600)
Lake Snow	3.040*	3.039*	3.039*	3.119*	3.038*	3.045*	3.058*
	(1.792)	(1.792)	(1.792)	(1.790)	(1.790)	(1.787)	(1.766)
Sleet	-0.215	-0.215	-0.215	-0.175	-0.226	-0.256	-0.283
	(0.192)	(0.192)	(0.192)	(0.185)	(0.184)	(0.201)	(0.208)
Winter Weather	0.607	0.606	0.606	0.618	0.557	0.533	0.524
	(0.450)	(0.450)	(0.449)	(0.424)	(0.407)	(0.382)	(0.360)
Constant	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***
	(0.000536)	(0.000642)	(0.000763)	(0.000600)	(0.000513)	(0.000582)	(0.000797)
Year FE	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y
Observations	12,839,152	12,262,021	11,674,623	11,092,951	10,504,887	9,338,347	8,171,807
R^2	0.224	0.224	0.224	0.213	0.219	0.228	0.223

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Dependent variable is log of normalized property damage.
Frequency is 3-year rate with specified lag.

B.2 Frequency time period

Tables B.6 - B.10 report the results for our measure of frequency averaged over different time periods. The coefficient estimates are reasonably stable across the specifications.

Table B.6: Flood Results, Different Frequency Time Periods

	(1)	(2)	(3)	(4)	(5)	(6)
Frequency (1yr avg)	-0.000344***					
	(0.000127)					
Frequency (2yr avg)		-0.000804***				
		(0.000271)				
Frequency (3yr avg)			-0.00107**			
			(0.000424)			
Frequency (4yr avg)				-0.00141***		
				(0.000457)		
Frequency (5yr avg)					-0.00152***	
					(0.000417)	
Frequency (6yr avg)						-0.00140**
						(0.000598)
Duration	0.00527***	0.00528***	0.00528***	0.00514***	0.00506***	0.00532***
	(0.00159)	(0.00166)	(0.00166)	(0.00166)	(0.00158)	(0.00170)
Coast Flood	3.021***	2.992***	2.993***	3.005***	3.001***	3.007***
	(1.057)	(1.067)	(1.067)	(1.072)	(1.072)	(1.081)
Flash Flood	2.650***	2.557***	2.557***	2.491***	2.464***	2.485***
	(0.203)	(0.208)	(0.208)	(0.209)	(0.211)	(0.225)
Flood	2.538***	2.506***	2.506***	2.567***	2.626***	2.707***
	(0.301)	(0.272)	(0.272)	(0.278)	(0.273)	(0.299)
Lake Flood	8.872***	8.872***	8.870***	8.899***	8.917***	8.865***
	(0.546)	(0.556)	(0.556)	(0.560)	(0.556)	(0.563)
Constant	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***
	(0.00177)	(0.00149)	(0.00153)	(0.00168)	(0.00217)	(0.00233)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Observations	14,003,143	12,836,968	11,674,619	10,504,884	9,338,344	8,171,804
R^2	0.314	0.309	0.309	0.308	0.311	0.320

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Dependent variable is log of normalized property damage.
Frequency is rate over specified period with a 1-year lag.

Table B.7: Hail Results, Different Frequency Time Periods

	(1)	(2)	(3)	(4)	(5)	(6)
Frequency (1yr avg)	-4.13e-05					
	(7.32e-05)					
Frequency (2yr avg)		-6.24e-05				
		(0.000130)				
Frequency (3yr avg)			-7.33e-05			
			(0.000173)			
Frequency (4yr avg)				-6.14e-05		
				(0.000218)		
Frequency (5yr avg)					-5.49e-05	
					(0.000256)	
Frequency (6yr avg)						-8.56e-05
						(0.000283)
Magnitude	0.937***	0.937***	0.937***	0.937***	0.937***	0.961***
	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)	(0.135)
Constant	-20.73***	-20.73***	-20.73***	-20.73***	-20.73***	-20.72***
	(0.00117)	(0.00120)	(0.00121)	(0.00122)	(0.00123)	(0.000843)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Observations	27,991,887	27,991,887	27,991,887	27,991,887	27,991,887	26,833,191
R^2	0.150	0.150	0.150	0.150	0.150	0.154

Robust standard errors in parentheses

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

Dependent variable is log of normalized property damage.

Frequency is rate over specified period with a 1-year lag.

Table B.8: Tornado Results, Different Frequency Time Periods

	(1)	(2)	(3)	(4)	(5)	(6)
Frequency (1yr avg)	-0.000130***					
	(4.48e-05)					
Frequency (2yr avg)		-0.000218**				
		(0.000103)				
Frequency (3yr avg)			-0.000286**			
			(0.000130)			
Frequency (4yr avg)				-0.000410**		
				(0.000178)		
Frequency (5yr avg)					-0.000474***	
					(0.000175)	
Frequency (6yr avg)						-0.000575***
						(0.000213)
Tornado F-0	3.541***	3.541***	3.541***	3.541***	3.541***	3.552***
	(0.343)	(0.343)	(0.343)	(0.343)	(0.343)	(0.341)
Tornado F-1	9.319***	9.319***	9.319***	9.319***	9.319***	9.259***
	(0.396)	(0.396)	(0.396)	(0.396)	(0.396)	(0.395)
Tornado F-2	12.01***	12.01***	12.01***	12.01***	12.01***	11.87***
	(0.414)	(0.414)	(0.414)	(0.414)	(0.414)	(0.423)
Tornado F-3	14.28***	14.28***	14.28***	14.28***	14.28***	14.19***
	(0.251)	(0.251)	(0.251)	(0.251)	(0.251)	(0.262)
Tornado F-4	15.79***	15.79***	15.79***	15.79***	15.79***	15.71***
	(0.408)	(0.408)	(0.408)	(0.408)	(0.408)	(0.390)
Tornado F-5	17.04***	17.04***	17.04***	17.04***	17.04***	17.04***
	(0.689)	(0.689)	(0.689)	(0.689)	(0.689)	(0.689)
Constant	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***
	(0.000273)	(0.000276)	(0.000281)	(0.000288)	(0.000285)	(0.000718)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Observations	28,002,557	28,002,557	28,002,557	28,002,557	28,002,557	26,843,498
R^2	0.709	0.709	0.709	0.709	0.709	0.702

Robust standard errors in parentheses

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

Dependent variable is log of normalized property damage.

Frequency is rate over specified period with a 1-year lag.

Table B.9: Wind Results, Different Frequency Time Periods

	(1)	(2)	(3)	(4)	(5)	(6)
Frequency (1yr avg)	-0.000965***					
	(0.000270)					
Frequency (2yr avg)		-0.00103**				
		(0.000415)				
Frequency (3yr avg)			-0.000780			
			(0.000625)			
Frequency (4yr avg)				0.000242		
				(0.000617)		
Frequency (5yr avg)					0.000757	
					(0.000929)	
Frequency (6yr avg)						0.00144
						(0.00111)
Magnitude	0.0569***	0.0570***	0.0570***	0.0604***	0.0625***	0.0675***
	(0.00951)	(0.00931)	(0.00931)	(0.00981)	(0.0102)	(0.0102)
High Wind	-0.0590	-0.0433	-0.0429	-0.0893	-0.0843	-0.156
	(0.162)	(0.167)	(0.167)	(0.170)	(0.179)	(0.197)
Strong Wind	4.482***	4.495***	4.494***	4.371***	4.288***	4.096***
	(0.522)	(0.521)	(0.521)	(0.529)	(0.537)	(0.536)
Constant	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***
	(0.000485)	(0.000534)	(0.000698)	(0.000784)	(0.000938)	(0.00106)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Observations	14,001,783	12,836,172	11,672,495	10,503,470	9,337,622	8,171,792
R^2	0.473	0.481	0.481	0.497	0.512	0.530

Robust standard errors in parentheses

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

Dependent variable is log of normalized property damage.

Frequency is rate over specified period with a 1-year lag.

Table B.10: Winter Results, Different Frequency Time Periods

	(1)	(2)	(3)	(4)	(5)	(6)
Frequency (1yr avg)	-0.000488					
	(0.000304)					
Frequency (2yr avg)		-0.000941**				
		(0.000382)				
Frequency (3yr avg)			-0.00136**			
			(0.000520)			
Frequency (4yr avg)				-0.00144**		
				(0.000578)		
Frequency (5yr avg)					-0.00109*	
					(0.000562)	
Frequency (6yr avg)						-0.000966
						(0.000785)
Duration	0.0174	0.0130	0.0130	0.0131	0.0127	0.0121
	(0.0121)	(0.0126)	(0.0126)	(0.0113)	(0.0110)	(0.0102)
Blizzard	1.158*	1.213*	1.213*	1.132**	1.157**	1.143**
	(0.686)	(0.687)	(0.687)	(0.528)	(0.507)	(0.474)
Ice Storm	3.330***	3.577***	3.578***	3.555***	3.777***	3.757***
	(0.631)	(0.586)	(0.586)	(0.599)	(0.602)	(0.600)
Lake Snow	2.763	3.040*	3.039*	3.038*	3.045*	3.058*
	(1.794)	(1.792)	(1.792)	(1.790)	(1.787)	(1.766)
Sleet	-0.278	-0.215	-0.213	-0.227	-0.257	-0.283
	(0.185)	(0.192)	(0.192)	(0.184)	(0.201)	(0.208)
Winter Weather	0.533	0.606	0.606	0.557	0.533	0.524
	(0.427)	(0.450)	(0.449)	(0.407)	(0.382)	(0.360)
Constant	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***	-20.72***
	(0.000478)	(0.000552)	(0.000740)	(0.000514)	(0.000547)	(0.000657)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Observations	14,005,327	12,839,152	11,674,623	10,504,887	9,338,347	8,171,807
R^2	0.223	0.224	0.224	0.219	0.228	0.223

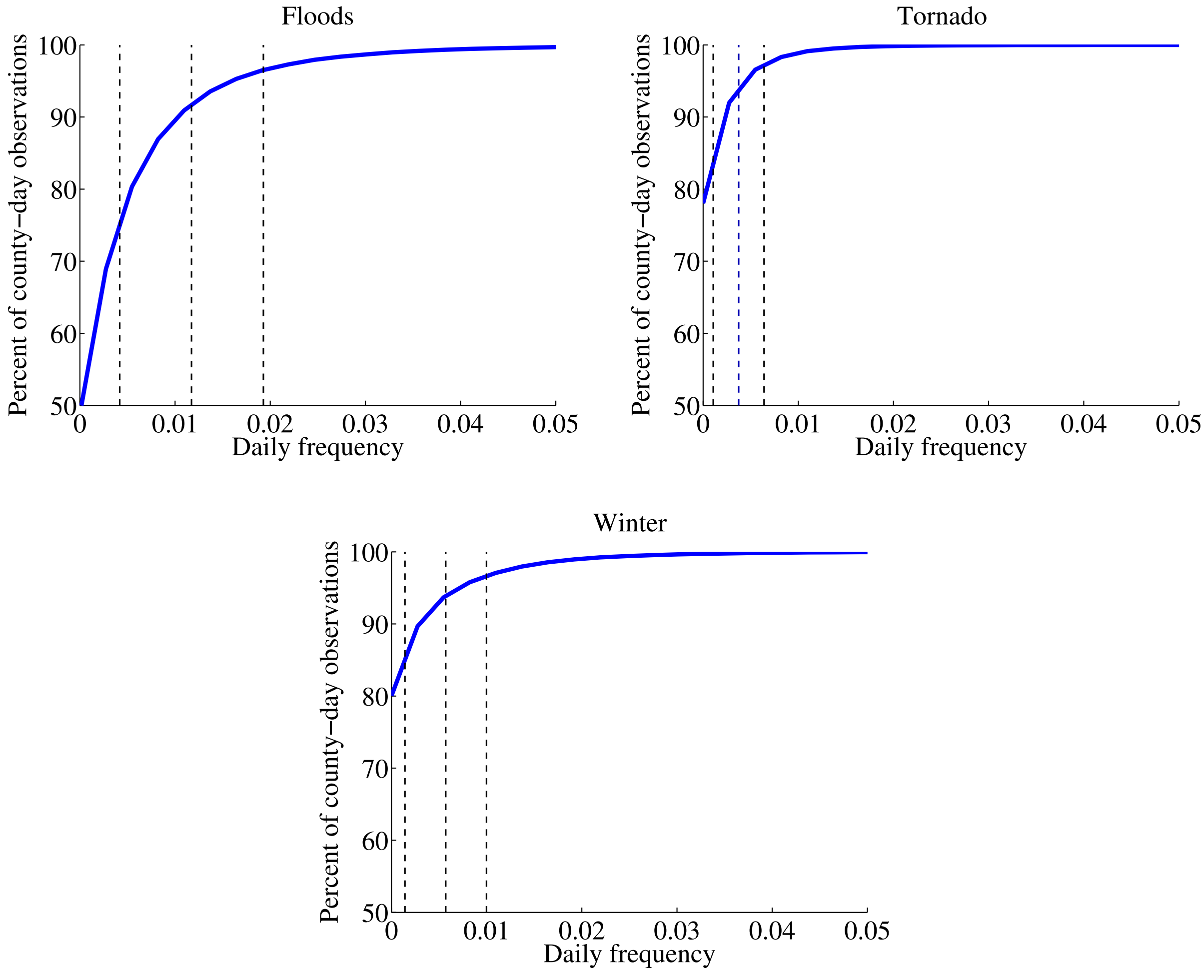
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Dependent variable is log of normalized property damage.
Frequency is rate over specified period with a 1-year lag.

C Additional figures

Each panel in Figure C.1 shows the cumulative distribution of daily event frequency across all county-day observations for each category of extreme weather event. The dashed lines show the mean daily frequency, the mean plus one standard deviation and the mean plus two standard deviations.

Figure C.1: Cumulative Distribution of Daily Event Frequency



Note: The dashed lines represent the mean daily frequency, the mean plus one standard deviation, and the mean plus two standard deviations for each weather category.