Risk and Adaptation: Evidence from Global Hurricane Damages and Fatalities

Journal:	*American Economic Review*
Manuscript ID:	Draft
Manuscript Type:	Regular Submission - High Income Country - Member
Keywords:	Q54, H12, D81

Disclosure Statement

By Laura A. Bakkensen

The author declares that she has no conflict of interest relating to the research described in this paper. The author discloses that in 2010, she received a $5,000 Doctoral Student Research Support grant from the Yale Institute of Biospheric Studies and applied a portion of the funds to research for this paper.

Disclosure Statement

By Robert O. Mendelsohn

The author declares that he has no conflict of interest relating to the research described in this paper. The author discloses that the simulation data used to calculate the underlying frequency of storm landfalls was purchased from WindRiskTech, LLC through funding by the World Bank during a previous project.

Risk and Adaptation: Evidence from Global Hurricane Damages and Fatalities

By Laura A. Bakkensen and Robert O. Mendelsohn

We examine whether countries adapt to hurricanes. A spatially refined global tropical cyclone data set is created to test for adaptation. We find evidence of adaptation in most of the world by examining the effects of income, population density, and storm frequency on damage and fatalities. In contrast, there is no evidence of adaptation to damage in the United States leading to a damage function which is twenty times higher than the rest of the world. (JEL D81, O1, O2, Q54, Q56, R5)

Economists are well aware that people and firms adapt to risk. People use smoke detectors to protect themselves from residential fire (Dardis, 1980), seat belts to protect themselves from accidents (Atkinson and Halvorsen, 1990), and sunscreen to protect themselves from melanoma (Dickie and Gerking, 1996). But how much adaptation do individuals, firms, and governments already undertake to cope with the risks of natural disasters? The expected annual global damage from tropical cyclones (hurricanes) is $26 billion dollars plus 19,000 lives lost (Mendelsohn et al., 2012; CRED, 2012). Is this with or without adaptation? If there is adaptation, how much damage and fatality has been avoided?

In the absence of official government programs, the literature on tropical cyclones commonly assumes that there currently is no adaptation. They assume that damage is proportional to what is in harm's way and increases proportionally with GDP (damage is proportional to both income and population) (Hsiang and Narita, 2012; Nordhaus, 2010; Pielke et al., 2008; Pielke and Landsea, 1998). This assumption is a natural extension of controlled experiments where damage in a wind tunnel increases in unison with capital in harm's way. The literature is more ambiguous about fatalities where there has long been evidence of adaptation but even here there are some studies that assume fatalities increase proportionately with population (Hsiang and Narita, 2012). But do people, firms, and governments with property at risk and lives at stake take no effective measures to protect their assets and themselves from catastrophic events such as tropical cyclones? Or do people only protect themselves from private risks such as fire and automobile accidents?

We test the adaptation hypothesis using two approaches. First, we estimate the elasticity of income with respect to the damage and fatalities from tropical cyclones around the globe. If the income elasticity of damage is unitary or if the income elasticity of fatalities is zero, this would support the hypothesis of no adaptation. Second, we compare tropical cyclone damage in the United States to tropical cyclone damage in the rest of the world. The United States receives an average of 4 percent of global landfalls but incurs one third of global damages[1]. We argue that there is no adaptation in the United States because households, firms, and local governments are compensated for economic damage from tropical cyclones using a combination of subsidized national flood insurance, state regulations on coastal property insurance rates, and generous post disaster relief programs. House-

[1]Calculated by the authors using data from the Centre for Research on the Epidemiology of Disasters (CRED, 2012).

holds, firms, and local governments have virtually no incentive to adapt to the economic damage from tropical cyclones in the United States. Such relief programs are at much smaller scales in the rest of the world. The consequence of adaptation can be measured by contrasting the damage from storms in the United States with the damage in the rest of the world controlling for storm intensity, population, and income. Of course, the United States does not have a program that compensates for lives lost. So only the property damage and not the fatalities from tropical cyclones are different in the United States.

We formally test the adaptation hypothesis by gathering spatially-explicit data on 1,400 tropical cyclone landfalls from 1960 until 2010 that have struck inhabited areas around the world. We match information about the strength of these storms as well as the income and population density of the places where the hurricanes hit. We then regress the observed damage and fatalities from these storms on the hurricane strength as well as the population density and income of the affected area. We also compute the historic rate of low and high intensity storms for each area and explore to what degree prior experience affects the impacts per storm.

We find ample evidence of adaptation to fatalities across the world. The income elasticity to fatalities is quite negative. We also find evidence of adaptation to economic damage in every country except the United States. The income elasticity of damage in the rest of the world lies between 0.6 and -2.3. All of these values are statistically significantly less than unitary. In contrast, the income elasticity of damage in the US lies between 1 and 1.6. The hurricane damage in the United States is about 20 times higher than the rest of the world. If the United States had the same damage coefficients as the rest of the world, the expected annual American damage from hurricanes would be \$0.47 billion instead of the observed \$9 billion. If the rest of the world had the same damage coefficients as the United States, global damage would be \$522 billion per year instead of the observed \$26 billion. The results suggest that a great deal of the potential damage from tropical cyclones has been eliminated by adaptation, except in the United States.

I. Theory

Faced with a set of risks, individuals, and governments often take steps to protect themselves. Adaptation drives a wedge between observed and potential damage and fatalities (Brooks, 2003; Fankhauser and McDermott, 2013). To empirically identify this adaptive wedge between observed and potential losses, we characterize the distribution of human population and capital stock in harm's way. Gridded global population data are available (Dobson et al., 2000; Bhaduri et al., 2002; CIESIN et al., 2005) but spatially-explicit census data on the global capital stock across time are not available. Several proxy databases exist (Nordhaus, 2006; De Bono, 2013) but the predicted detailed spatial distribution is driven mainly by population rather than income per capita.

We follow the literature by predicting the capital stock from population and income. We calculate the ratio between capital and per capita gross domestic product (GDP per capita) to be 2.65 using 2005 country-level data from the World Bank[2]. This is similar to the 2.8 value from Hallegate et al. (2013) and the 3.1 value from Kamps (2004) but well below the 5 value

[2] R^2 value of 0.96.

assumed by Hansen et al. (2011). Thus, the empirical evidence supports the assumption that the capital stock scales proportionately with income and population[3]. We consequently assume the per capita capital stock, K, is

$$K = 2.65Y$$

where Y is income per capita.

The potential damage per storm, PD_x, is the damage expected in the absence of adaptation. It is determined by the per capita capital stock, K, the population struck by the storm, Pop, and the intensity of the storm, I. For a storm of a given physical size, we measure the population struck by that storm using the population density of the affected location. We use two measures of intensity, minimum pressure and maximum wind speed. We assume damage in the absence of adaptation to have the following functional form:

$$PD_x = \alpha_0 Y Pop I^{\alpha_3}$$

Similarly, we assume that potential fatalities per storm, PF_x, has the following functional form with respect to storm intensity, I, and population density, Pop:

$$PF_x = \beta_0 Pop I^{\beta_3}$$

Increases in population will lead to proportional increases in potential fatalities. With no adaptation, income does not enter the potential fatalities function. People of every income are equally likely to die if nobody takes precautions. The parameters, α and β, are assumed to be positive implying an increase in any of the above factors are expected to increase potential

[3]Graphs and additional supporting evidence are available in the Online Appendix.

impacts, including increases in income ($\frac{dPD}{dY} > 0$), increases in population density ($\frac{dPD}{dPop} > 0$ and $\frac{dPF}{dPop} > 0$), and increases in storm intensity ($\frac{dPD}{dI} > 0$ and $\frac{dPF}{dI} > 0$).

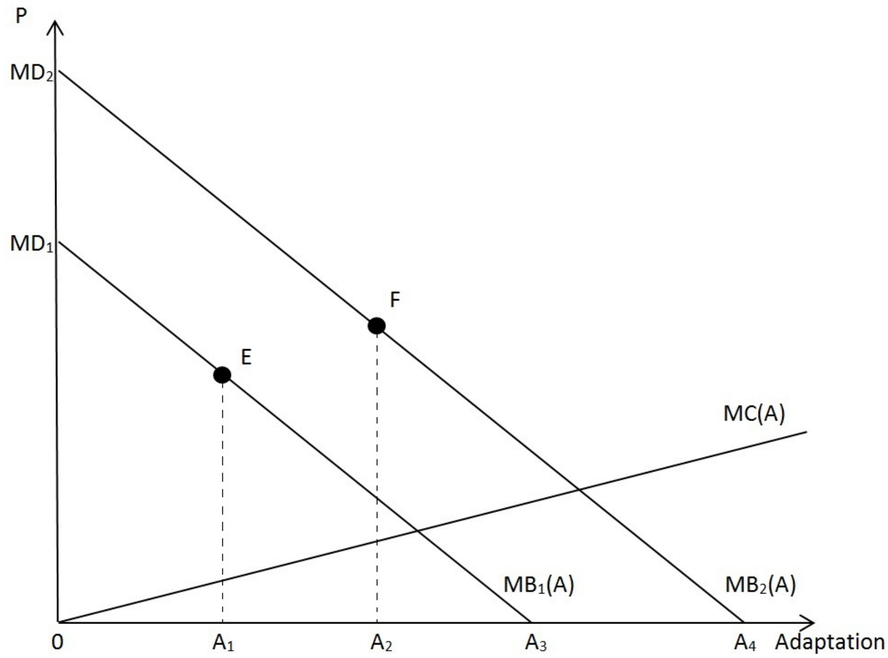
We next assume that individuals choose some level of adaptation, A, with benefit $B(A)$ and cost $C(A)$. Assuming that the adaptation benefit and cost functions are well behaved[4], the optimal adaptation, A^*, occurs when the marginal benefit equals the marginal cost, $MB(A^*) = MC(A^*)$. We do not assert that adaptation is necessarily efficient in this paper. We simply test whether individuals, firms, and governments respond to higher levels of benefits of adaptation by doing more adaptation. That is, we assume actors choose some nonzero level of adaptation denoted by A_1 based on the marginal damage curve MD_1 in Figure 1. With adaptation level A_1, the total observed damage equals the area of triangle A_1EA_3 whereas the total potential damage (with no adaptation) is triangle $0MD_1A_3$. The fraction of damage removed to the potential damage ($\theta(A)$) is $\theta(A) = (0MD_1EA_1)/(0MD_1A_3)$. Note that the removed damage is not the welfare gain of adaptation. The welfare gain of adaptation A_1 is the area below the $MB_1(A)$ and above $MC(A)$ curve, as one must subtract the adaptation cost[5]. Observed damage, D_x, is the product of potential damages times the fraction of damage removed by adaptation: $D_x = \theta(A) \cdot PD_x$.

Several factors can shift the MB(A) curve, from $MB_1(A)$ to $MB_2(A)$ in Figure 1, impacting the level of potential and observed damages. The

[4]The first and second order conditions required for an interior solution are presented in a model of optimal adaptation in the Online Appendix.

[5]There terms can be equivalently defined by the following integrals: $\int_{A_1}^{A_3} MB_1(A)dA$ for observed damage, $\int_0^{A_3} MB_1(A)dA$ for potential damage, and $\frac{\int_0^{A_3} MB_1(A)dA - \int_{A_1}^{A_3} MB_1(A)dA}{\int_0^{A_3} MB_1(A)dA}$ for the adaptation impact $\theta(A)$.

Figure 1. Marginal Costs and Marginal Benefits of Adaptation



marginal benefit of adaptation increases with income, population, storm intensity, and underlying storm frequency (Π). Under an efficient solution, this would also increase the equilibrium level of adaptation. However, we do not require optimality, we simply test whether $A_2 > A_1$. That is, we test whether adaptation increases as income, population density, or storm frequency increases ($\frac{dA}{dY} > 0$), ($\frac{dA}{dPop} > 0$)[6], ($\frac{dA}{d\Pi_l} > 0$) and ($\frac{dA}{d\Pi_h} > 0$). We specifically examine the effect of predicted frequencies of both low (Π_l) and high (Π_h) intensity storms. Incorporating potential demand shifters, we approximate $\theta(A)$ with the following constant elasticity functional form:

$$\theta(A) \approx (1-\gamma_0)Y^{-\gamma_1}Pop^{-\gamma_2}I_x^{-\gamma_3}\Pi_l^{-\gamma_4}\Pi_h^{-\gamma_5}$$

[6]This may be especially true if public adaptation is focused on areas with more people, but if adaptation costs increase in population, then there may be no increase in adaptation.

The γ_i terms equal zero if there is no adaptation. The observed damage will have the following expression:

$$D_x = \alpha_0(1-\gamma_0)Y^{1-\gamma_1}Pop^{1-\gamma_2}I_x^{\alpha_3-\gamma_3}\Pi_l^{-\gamma_4}\Pi_h^{-\gamma_5}$$

Similarly, observed fatalities, F_x, from storm x are the multiplicative product of potential damages and adaptation, $F_x = \theta(A) \cdot PF_x$:

$$F_x = \beta_0(1-\gamma_0)Y^{-\gamma_1}Pop^{1-\gamma_2}I_x^{\beta_3-\gamma_3}\Pi_l^{-\gamma_4}\Pi_h^{-\gamma_5}$$

This is effectively a dynamic test for adaptation. It explores whether adaptation increases as factors that would increase the potential benefits of adaptation increase. If no adaptation is present in economic damage and fatalities, then $\gamma_i = 0$ for $i = \{0, 1, 2, 3, 4, 5\}$. Whether $\gamma_i > 0$ is a testable hypothesis for the existence of adaptation. That is, adaptation is present in economic damage to the extent that the income elasticity and population elasticity are less than unitary (1). Adaptation would also be evident if the historic frequency of storms lowers the damage per storm. Similarly, adaptation is present in fatalities if the elasticity of income is negative, the elasticity of population is less than one, or the elasticity with respect to frequency is negative. Unfortunately, the potential coefficient on the constant term and on the intensity of storms is not known and so cannot be used to test for adaptation.

Because the United States has subsidized flood insurance, ample post storm compensation, and regulations on traditional insurance premiums along the coast, individuals, firms, and local governments face very low costs for being in harm's way. Their insurance premiums for the additional risk are near zero and they are often compensated for damage that is not insured. Owners of both governmental and private capital along the coast in the United States have no incentive to adapt to the risk of tropical cyclones. This policy "experiment" of the United States offers a second opportunity to test for adaptation. We postulate that the damage function for the United States reflects potential damage (zero abatement). The rest of the world does not offer such generous compensation programs. Another test of adaptation is therefore the difference between the parameters of the United States damage function and the parameters of the damage function for the rest of the world. The damage function of the United States should resemble the potential damage function whereas the damage function of the rest of the world resembles the adaptation damage function. Note that we are not assuming perfectly efficient adaptation in the rest of the world, just more extensive adaptation. Because the United States does not compensate people for dying in a tropical cyclone, the United States is not expected to have different fatality coefficients, just different damage coefficients. One of the additional benefits of this second test is that both the constant term and the coefficient on intensity can also be examined.

For both of these tests of adaptation, we are assuming that there are many possible actors that can adapt including households, firms, and farms as well as local and state governments. We are assuming that private actors focus on reducing just their own damages, while governments focus on reducing the damages to all the people in their jurisdiction. This analysis does not distinguish who is doing the adaptation. We therefore are examining the adaptation of both private individuals and firms as well as local governments. Lastly, we do not know to what extent adaptation to economic damage is a complement or substitute to adaptation to fatalities.

II. Empirical Strategy

Guided by the theoretical framework above, we use panel data to test for the presence of adaptation to tropical cyclone damages and fatalities. We first estimate damage and fatality functions using a log-log functional form through cross-sectional and panel techniques[7]. Resulting estimated coefficients can be interpreted as elasticities. We then test to see if these elasticities are below theoretical thresholds (evidence of adaptation). We also test if adaptation levels vary across income levels by estimating respective damage and fatality elasticities on partitioned samples including only low or high income countries. Finally, we test the elasticities of the United States compared to the rest of the world[8].

We use both a cross-sectional model and error components model with country and time fixed effects to calculate damage and fatality functions. Cross-sectional analysis uses variation across time and countries to identify parameters of interest, whereas identifying variation for our error components model occurs in deviations from country and year averages. Broadly, cross-sectional results can shed light on long-run patterns of adaptation (Mendelsohn et al., 1994). To the extent that some adaptation changes very slowly over time, within-country and within-year variation will not capture adaptive changes on these broader scales. However, cross-sectional analysis may be confounded by time- and location-specific omitted variable

[7]Count data estimation results are shown in the Online Appendix. The results support the findings of our cross-sectional and error components models.

[8]See the Online Appendix for a discussion potential econometric concerns and for a detailed explanation of specification tests and explanatory variable choice.

bias that our error components model will subsume. Lastly, panel data and cross-sectional results often have a different economic interpretation, as short term shocks are different than long term adaptive potential (Timmins and Schlenker, 2009; Samuelson, 1947). Due to the strengths and weaknesses of each technique, we present both models herein.

After specification and model selection testing presented in the Online Appendix, including linear and semi-log functional forms as well as additional variables, we chose the following log-log functional form for its goodness of fit to model damages for cyclone landfall j at time t in country i:

$$lnD_{ijt} = \alpha_0 + \alpha_1 lnY_{it} + \alpha_2 lnPop_{it} + \alpha_3 lnI_{ijt} + \alpha_4 lnL_{ijt} + \alpha_5 ln\Pi_{hi} + \alpha_6 ln\Pi_{li} + \alpha_i + \gamma_t + u_{ijt}$$

and for fatalities:

$$lnF_{ijt} = \beta_0 + \beta_1 lnY_{it} + \beta_2 lnPop_{it} + \beta_3 lnI_{ijt} + \beta_4 lnL_{ijt} + \beta_5 ln\Pi_{hi} + \beta_6 ln\Pi_{li} + \alpha_i + \gamma_t + u_{ijt}$$

where D_{ij} is total damages and F_{ij} is the number of fatalities. These impacts are explained by Y_{it}, the income per capita in country i at the time of cyclone j; Pop_{it}, the population density; I_{ijt}, the intensity of cyclone j when making landfall in country i; Π_{li}, the long-term frequency of low intensity storms in country i; and Π_{hi}, the long-term frequency of high intensity storms in country i. L_{ij}, a variable for landfall, is 1 if the cyclone j made a direct landfall on the country i and otherwise equal to the distance in kilometers of the storms' closest approach. In the error components model, we also include fixed effects for time (γ_t) and country (α_i). u_{ijt} is a mean-zero error term. Explanatory variables are identical between the cross sectional and fixed effects specification except for the year, γ_t, and country, α_i, fixed effects which subsume the high and low intensity cyclone frequency variables.

We estimate both functions using the Ordinary Least Squares (OLS) estimator. We also cluster standard errors at the country level in all specifications unless noted otherwise, to account for any within-country correlation across error term observations[9]. Unlike previous literature that aggregates up to the country-year level (Hsiang and Narita, 2012; Neumayer, 2012; Noy, 2009; Kahn, 2005), our unit of observation is a country-landfall (a storm striking a country). This ensures that any missing storms are not treated as zero, which could bias estimated coefficients. We also do not normalize cyclone impacts by population or income, which would imply no adaptation. Thus, we directly explain impact magnitudes on a per-landfall level.

In the Online Appendix, we present count data technique results for fatalities, estimating semi-log regressions with the Negative Binomial estimator. We test for and find evidence of over-dispersion in the data, implying that the Negative Binomial estimator is preferred to the Poisson. We do not use count data techniques for damages as they are closer to being normally distributed. Fixed effects negative binomial results are included, but should be interpreted with caution as there is still some debate in the literature as to proper implementation of the fixed effect controls (Greene, 2007). The results support the findings of our cross-sectional and fixed effects results.

For the empirical analysis, we build an original dataset of more than 1,400 storm landfalls around the Earth from 1960 to 2010 totaling almost $USD 0.75 trillion in damages and approximately 400,000 lives lost. All dollar values in this paper are in terms of real 2010 $USD. Historical cyclone

[9]Ferreira et al. (2013) note the importance of country-clustered standard errors for cross-country disaster analyses.

landfall damages and fatalities records from EM-DAT Emergency Disaster Database (CRED, 2012) and Nordhaus (2010) are matched with tropical cyclone characteristics compiled by NOAA IBTrACS v03r03, U.S. Navy Tropical Cyclone Reports, and Nordhaus (2010). Both maximum wind speed and minimum sea level pressure are tested as proxies for cyclone intensity. Country-level population and income data come from the Penn World Table v7.01, USDA ERS International Macroeconomic Data, the CIA World Factbook, and Columbia CIESIN's Gridded Population of the World v3. For six of the larger countries affected by storms (Australia, China, India, Japan, Philippines, and United States), income and population is measured at the county level and for Mexico at the state level using official census records. This allows a closer fit between where storms land and what is impacted. We test both market exchange rate and purchasing power parity definitions for income per capita. Finally, given current climate, a hurricane generator is used to predict the long-term frequency for low and high intensity storm landfalls for each location. A total of 68,000 simulated cyclone tracks generated by Kerry Emanuel are used to predict the frequencies by location (Emanuel et al. 2006). For the purposes of this analysis, low intensity storms have 10-minute sustained maximum wind speeds that rank them between a tropical depression and Category 3 strength (34 to 115 knots). High intensity storms include all Category 4 and 5 storms (greater than 115 knots), based on wind speed (NHC, 2012). We present the summary statistics of the sample in our Online Appendix[10]. All together, 87 countries are struck by tropical cyclones and are represented. Only observed landfalls are included in the database, locations with no storms are omitted from our

[10]A detailed description of data sources is available from the author.

analysis.

With any data, measurement error is possible. In this analysis, measurement error is a potential concern in both the damage and fatality data (EM-DAT) and the cyclone intensity (IBTrACS) data. Both are addressed herein. The damage and fatality data is likely the largest source of potential classical measurement error and even strategic reporting bias. The former will cause no bias in the regression coefficients but the latter may cause a bias toward zero if harm is underreported. See the Online Appendix for a proof of this measurement error result. We control for potential strategic reporting through selective sub-sample regressions based on income. As discussed in the Online Appendix and the Results section, we control for problems with storm intensity data by placing more emphasis on minimum sea level pressure rather than maximum wind speed as a measure of cyclone intensity because it more closely predicts damage. It is likely that minimum sea level pressure is measured with greater accuracy than wind speed (Gray et al., 1991).

Another important issue is that of selection of observations into our analysis sample. EM-DAT is arguably one of the best sources for global natural disaster data available and verification of data quality is an important step in their entry procedures (Tschoegl et al., 2006; Guha et al., 2002). However, not all historical cyclone landfalls are included in the EM-DAT database and not all cyclones in the database have a record of both damage and fatalities. EM-DAT censors low impact storms with minimum damage and fatality criterion[11]. However, the definition of a tropical cyclone itself cen-

[11]A cyclone must meet at least one of the following criterion to be included in EM-DAT: 1) 10 or more fatalities, 2) 100 or more people affected, 3) a declaration of a state of emergency, or 4) a call for international assistance (CRED, 2012).

sors storms below a critical intensity. It is possible this censorship affects the parameters but this censorship is not expected to have a large effect on the overall results because few fatalities and little damage are caused by low intensity storms.

III. Results

This section presents our main results using cross-sectional and fixed effects specifications. Results for alternative specifications, functional forms, and sensitivity analyses are presented in the Online Appendix.

A. Fatalities

Table 1 shows the regression results for fatalities using all countries. Columns 1, 2, and 3 are cross-sectional regressions. Column 1 presents a basic regression. Column 2 decomposes the cyclone frequency into low, Π_L, and high, Π_H, intensity storms. Column 3 uses maximum wind speed instead of minimum sea level pressure as a proxy for storm intensity. Columns 4 and 5 add a year fixed effect. Columns 6 and 7 add a country fixed effect.

Note that the t-statistic on observed coefficients may be used to test if estimated elasticities are statistically different from zero. We use the F-test to test if relevant elasticities are statistically different from one. The signs of covariate estimated elasticities are as we expected, with fatalities rising with lower minimum sea level pressure and higher maximum sustained wind speed, I. Fatalities decrease as the distance from the eye of the storm increases.

Table 1—Evidence of Adaptation to Fatalities

Dependent Variable: Log Fatalities

Regression	(1) Base	(2) Π Split	(3) Wind	(4) Year FE	(5) Year FE, Wind	(6) Country FE	(7) Country FE, Wind
Ln Income Per Capita (Y)	-0.618***	-0.651***	-0.653***	-0.618***	-0.611***	-0.218***	-0.135*
	(0.0834)	(0.0886)	(0.0871)	(0.0868)	(0.0863)	(0.0738)	(0.0684)
Ln Population Density (Pop)	0.146*	0.132*	0.106	0.145*	0.121	0.228***	0.224***
	(0.0786)	(0.0772)	(0.0817)	(0.0870)	(0.0910)	(0.0509)	(0.0694)
Ln Intensity (I_x Pressure)	-9.189***	-9.429***		-8.270***		-10.54***	
	(2.777)	(2.791)		(2.905)		(2.355)	
Ln Intensity (I_x Wind Speed)			0.571***		0.384**		0.648***
			(0.145)		(0.175)		(0.139)
Ln Frequency All (Π)	0.0783*						
	(0.0416)						
Ln Frequency Low (Π_L)		0.257**	0.248**	0.279***	0.273***		
		(0.103)	(0.104)	(0.0996)	(0.0996)		
Ln Frequency High (Π_H)		-0.118*	-0.120*	-0.135**	-0.131**		
		(0.0673)	(0.0670)	(0.0653)	(0.0643)		
Ln Landfall Distance (L)	-0.162***	-0.158***	-0.157***	-0.149***	-0.151***	-0.141***	-0.139***
	(0.0231)	(0.0227)	(0.0222)	(0.0227)	(0.0232)	(0.0216)	(0.0219)
Constant	69.97***	70.86***	3.966***	63.35***	4.411***	77.76***	1.841*
	(19.53)	(19.67)	(1.140)	(20.49)	(0.946)	(16.36)	(0.986)
Year FE	N	N	N	Y	Y	Y	Y
Country FE	N	N	N	N	N	Y	Y
Observations	1,006	1,006	995	1,006	995	1,020	1,008
R-squared	0.235	0.243	0.229	0.297	0.290	0.234	0.241

Note: *** p<0.01, ** p<0.05, * p<0.1 All specifications have standard errors clustered at the country level.

Using our theoretical thresholds, we find strong evidence of adaptation to fatalities. The income elasticity with respect to fatalities is less than zero for all specifications. The income elasticity of fatalities lies between -0.618 and -0.135. This income elasticity of fatalities is consistent with the income elasticity of the value of statistical life, found at the global meta-level to be between 0.5 to 0.6 (Viscusi and Aldy, 2003; Viscusi, 1993). We reject the null hypothesis that the income elasticity is equal to zero for all specifications, and reject at the 93% confidence level for the more conservative specification in column 7 where the elasticity is closest to zero. We also find evidence of adaptation to fatalities with respect to population density. Using the F-test, we find that the estimated elasticities are all less than one at the 99% confidence level. Even though the elasticity is positive, urban areas are still a protective force for reducing fatalities as doubling population less than doubles fatalities. This may be a conscious urban policy of adaptation for example due to urban evacuation plans. Or this result could simply be a consequence of constructing dense and sturdy structures (Lindell et al., 2011; Whitehead, 2003).

We find a divided result for the underlying storm frequency. The frequency of high intensity storms elasticity is negative, $\beta_5 < 0$, implying adaptation. Keefer et al. (2001) find similar results with lower fatalities to earthquakes in areas hit more frequently. However, we find the opposite result for the frequency of low intensity storms, (Π_L), as the estimated elasticities are greater than zero, $\beta_4 > 0$. This finding is significant at the 95% confidence level in Column 2 through 5. Although this analysis does not specify the maladaptation mechanism, one possible explanation is that individuals suffer from warning fatigue. Frequent weak storms pose small risks that do not warrant dramatic responses. With frequent false alarms, people may stop taking even modest precautions. Lastly, since people react differently to low and high intensity storms, a variable characterizing overall frequency of storms, Π, hides this dichotomous relationship. Thus, we caution the use of a single variable to characterize underlying storm risk commonly used in the literature (Fankhauser and McDermott, 2013; Hsiang and Narita, 2012; Neumayer et al., 2013; Schumacher and Strobl, 2011; Keefer et al., 2011).

TABLE 2—EVIDENCE OF ADAPTATION TO DAMAGES

Dependent Variable: Log Damages

Regression	(1) Base	(2) Π Split	(3) Wind	(4) Year FE	(5) Year FE, Wind	(6) Country FE	(7) Country FE, Wind
Ln Income Per Capita (Y)	0.447**	0.420**	0.364**	0.403**	0.353**	0.027	0.123
	(0.196)	(0.185)	(0.175)	-0.187	(0.175)	(0.157)	(0.169)
Ln Population Density (Pop)	0.074	0.057	-0.001	0.061	-0.034	-0.052	-0.303**
	(0.128)	(0.126)	(0.154)	(0.126)	(0.154)	(0.207)	(0.133)
Ln Intensity (I_x Pressure)	-29.49***	-29.94***		-28.40***		-34.35***	
	(6.269)	(6.061)		(5.288)		(7.308)	
Ln Intensity (I_x Wind Speed)			1.869***		1.738***		1.997***
			(0.383)		(0.412)		(0.489)
Ln Frequency All (Π)	-0.0454						
	(0.101)						
Ln Frequency Low (Π_L)		0.169	0.239*	0.224	0.279**		
		(0.140)	(0.141)	(0.139)	(0.139)		
Ln Frequency High (Π_H)		-0.144	-0.170*	-0.171*	-0.189*		
		-0.0944	-0.0978	-0.090	-0.0957		
Ln Landfall Distance (L)	-0.414***	-0.413***	-0.364***	-0.393***	-0.349***	-0.360***	-0.317***
	(0.0528)	(0.0517)	(0.0606)	(0.0523)	(0.0560)	(0.0577)	(0.0627)
Constant	217.2***	219.3***	5.879**	208.9***	6.559**	254.7***	10.95***
	(42.63)	(41.31)	(2.701)	(35.44)	(2.928)	(49.76)	(3.135)
Year FE	N	N	N	Y	Y	Y	Y
Country FE	N	N	N	N	N	Y	Y
Observations	844	844	832	844	832	856	843
R-squared	0.223	0.227	0.212	0.282	0.270	0.246	0.233

Note: *** p<0.01, ** p<0.05, * p<0.1 Standard errors are clustered at the country level.

B. Damage

Table 2 shows the results of the damage regressions using data from all countries. The column specifications are identical to those of Table 1. Damage increases with the intensity of the storm[12] and decreases with distance from the eye. We find clear evidence of adaptation in the income elasticity with respect to damage. The income elasticity varies from .03 to .45. The estimated income elasticities are all significantly less than one, $\alpha_1 < 1$. We perform an F-test and reject (at the 99 percent confidence level) the unitary income elasticity of damages assumed by the previous literature (Hsiang and Narita, 2012; Nordhaus, 2010; Pielke et al., 2008; and Pielke and Landsea, 1998).

The population elasticity varies between -.3 and .07. These values are all significantly less than one, $\alpha_2 < 1$. As population density increases, damages do not increase. This result indicates damage per person falls in urban areas. Again this result may be due to conscious policies to adapt urban areas to storms or it may simply be an incidental result of more sturdy structures in urban areas.

Lastly, we find the elasticity of damage with respect to storm intensity to be lower than past literature. For example, the elasticity of minimum pressure is -29 to -34 whereas previous studies using data from the United States found values of -86 (Mendelsohn et al., 2012). The elasticity of damage with respect to maximum sustained winds is from 1.7 to 2 which is much closer to the traditional literature which found damage increases with the second or third power of wind speed (Emanuel, 2005; Bell et al., 2000; Pielke and

[12]Recall that minimum sea level pressure has an inverse relationship with intensity; a stronger storm has a lower pressure reading.

Landsea, 1999). In contrast, the empirical results from US data imply much higher elasticities of between 5 and 9 (Nordhaus, 2010; Mendelsohn et al., 2012).

Based on the Vuong (1989), AIC, and BIC tests, we prefer the use of minimum sea level pressure over wind speed[13]. It is likely that wind speed may be measured with greater error than minimum sea level pressure (Gray et al., 1991). Additionally, wind speed calculation techniques have changed over time without good documentation whereas minimum pressure reading techniques have remained consistent over time (Emanuel, 2013). Maximum wind speed is calculated differently throughout the world, with some calculated a 1-, 3-, or 10 minute sustained maximum wind speed. As there is no deterministic relationship between these sustained wind speeds, statistical averages must be used to convert them, leading measurements to diverge from the true values. Finally, some wind speed estimates across the world have been derived statistically from pressure readings whereas other measures have relied on rules of thumb making it difficult to track the source of wind data (NRL, 1998). Thus, we recommend the use of minimum sea level pressure readings to be utilized for damage and fatality research.

[13]We also test using both pressure and wind speed, but both variables become insignificant due to high multicollinearity.

TABLE 3—ADAPTATION TO FATALITIES: LOW AND HIGH INCOME COUNTRIES

Dependent Variable: Log Fatalities

	(1)	(2)	(3)	(4)	(5)	(6)
Income Level	<$6,500	<$6,500	<$6,500	>$20,000	>$20,000	>$20,000
Regression	Base	Decade FE	Country FE	Base	Decade FE	Country FE
Ln Income Per Capita (Y)	-0.447***	-0.406***	-0.001	-2.277***	-2.748***	-1.751**
	(0.146)	(0.131)	(0.119)	(0.369)	(0.511)	(0.621)
Ln Population Density (Pop)	0.361***	0.372***	0.291***	0.134	0.146	0.150**
	(0.0745)	(0.0786)	(0.0868)	(0.105)	(0.0894)	(0.0687)
Ln Intensity (I_x Pressure)	-13.59***	-11.68***	-13.01***	-7.266	-9.116*	-2.857
	(2.692)	(2.616)	(2.894)	(5.469)	(5.091)	(3.330)
Ln Landfall Distance (L)	-0.200***	-0.184***	-0.160***	-0.146***	-0.156***	-0.163***
	(0.0204)	(0.0213)	(0.0223)	(0.0394)	(0.0324)	(0.0472)
Constant	98.84***	85.69***	92.97***	74.47*	92.05**	39.51
	(18.93)	(18.16)	(20.46)	(38.65)	(36.80)	(24.39)
Decade FE	N	Y	Y	N	Y	Y
Country FE	N	N	Y	N	N	Y
Observations	579	579	579	152	152	152
R-squared	0.184	0.209	0.175	0.170	0.210	0.131

Note: *** p<0.01, ** p<0.05, * p<0.1 All specifications have standard errors clustered at the country level.

Table 4—Adaptation to Damages: Low and High Income Countries

Dependent Variable: Log Damages

	(1)	(2)	(3)	(4)	(5)	(6)
Income Level	<\$6,500	<\$6,500	<\$6,500	>\$20,000	>\$20,000	>\$20,000
Regression	Base	Decade FE	Country FE	Base	Decade FE	Country FE
Ln Income Per Capita (Y)	0.513***	0.606***	0.347*	-1.721*	-2.311*	-2.158**
	(0.178)	(0.194)	(0.204)	(0.994)	(1.118)	(0.793)
Ln Population Density (Pop)	0.405**	0.410**	0.003	0.008	-0.0237	0.510***
	(0.166)	(0.156)	(0.0763)	(0.175)	(0.180)	(0.147)
Ln Intensity (I_x Pressure)	-24.33***	-22.77***	-24.13***	-37.74***	-38.20***	-43.23***
	(4.132)	(3.874)	(3.421)	(12.15)	(13.31)	(11.44)
Ln Landfall Distance (L)	-0.394***	-0.398***	-0.382***	-0.540***	-0.543***	-0.659***
	(0.0501)	(0.0601)	(0.0508)	(0.161)	(0.164)	(0.116)
Constant	179.0***	168.5***	181.9***	295.4***	304.6***	334.9***
	(28.33)	(26.66)	(23.73)	(80.96)	(91.61)	(75.92)
Decade FE	N	Y	Y	N	Y	Y
Country FE	N	N	Y	N	N	Y
Observations	414	414	414	145	145	145
R-squared	0.230	0.251	0.201	0.256	0.278	0.284

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ All specifications have standard errors clustered at the country level.

C. Adaptation Across Income Levels

One hypothesis that has been raised with respect to adaptation is that adaptation capacity rises with income. We test this hypothesis in Tables 3 and 4 by examining whether the income elasticity of damage and fatalities is lower for higher income locations. We create sub-samples of the data for low income (<$6,500) and high income (>$20,000) locations. We then estimate separate regressions on each subsample. The United States is dropped as an outlier in this analysis. Table 3 reveals the results for fatalities. The columns vary depending upon the income of the locations and the use of fixed effects. Columns 1 and 4 are OLS regressions, columns 2 and 5 have decade fixed effects and columns 3 and 6 have both time and country fixed effects. Standard errors are clustered at the country level. To check the validity of the clustered standard errors for subsample regressions with fewer than fifty bins, we also calculate the coefficient p-values using wild bootstrapping as described by Cameron et al. (2008) and implemented in Stata with Caskey (2013). The significance of the results do not change. We use locations and not countries for this analysis. The included high (low) income locations come mainly from highly (lesser) developed countries and also wealthy urban centers (lower income rural areas) in developing and lesser developed countries, controlling also for population density. Therefore, differences are not driven by national policies but location-specific differences between wealthy versus poorer areas.

Low income locations have an income elasticity with respect to fatalities from 0 to -0.4 whereas high income locations have an income elasticity from -1.8 to -2.7. These results provide strong support for the idea that there is a lot of adaptation to prevent fatalities. Adaptation increases with income.

The high income location elasticities are statistically different from the elasticities of low income locations at the 99% confidence level. These very negative income elasticities of fatalities imply a much higher relationship between income and value of life compared to the literature (Viscusi and Aldy, 2003; Viscusi, 1993). The remaining coefficients of the fatality model are not different for the two subsamples.

Table 4 presents the damage results for low and high income locations. The columns in each damage regression are identical to those in Table 3 for fatalities. The income elasticity of damage for low income locations varies between 0.35 and 0.61 whereas the income elasticity varies between -1.7 and -2.3 for high income locations. All included countries show signs of adaptation to economic damage, and once again the results imply that adaptation increases rapidly with income. The damage income elasticity results are similar to the projections from an environmental Kuznets curve, with damages first increasing and then decreasing with income (Shafik, 1994). The estimated population, intensity, and distance coefficients are not statistically different between low and high income countries.

D. The United States

The United States has been dropped in earlier global studies of tropical cyclone damage because it is such an outlier (Hsiang and Narita, 2012). Here, we utilize the economic damage results from the United States as an example of potential damage (no adaptation). Table 5 compares the regression results using a sample of storms just from the United States, a sample just from OECD countries except the United States, and a sample just from non-OECD countries. Results for both minimum pressure and wind speed are presented.

All the coefficients of the United States regressions are significantly different from the coefficients of the other two samples. The income elasticity of the United States varies between 1.1 and 1.6 which is consistent with the theory that the model reflects the zero adaptation case. In contrast, the income elasticity for the remaining countries in the OECD lies between -0.5 and -0.6 and for the non-OECD countries between 0.2 and 0.3. The population density coefficient is negative for the United States whereas it is positive for the other OECD countries and zero for the non-OECD countries. This implies that American cities are relatively safer compared to rural areas. The discrepancy is more marked than in any other country. In contrast, the effect of intensity is higher in the United States than the rest of the world. Damages escalate rapidly with intensity in the United States. The elasticity with respect to minimum pressure is -85 for the United States but -34 for the rest of the OECD and -24 for non-OECD countries. Similar differences exist for wind speed. Finally, the constant term is much higher for the United States implying that all storms cause more damage.

Using these results, one can use the US coefficients as a counter-factual to see what damage in the rest of the world might have been if there was no adaptation. Similarly, one can use the coefficients for the rest of the world to determine what US damages would be with adaptation. If the United States had the same damage coefficients as the rest of the world, the annual tropical cyclone damages in the United States would average \$0.47 billion instead of the current \$9 billion. If the rest of the world had the same damage coefficients as the US, global damages would be \$522 billion per year instead of the current \$26 billion. There is a 20 fold difference between the estimated damage function for the US and the rest of the world.

Table 5—United States Damages

Dependent Variable: Log Damages

	(1)	(2)	(3)	(4)	(5)	(6)
Countries	USA	USA	OECD & non-USA	OECD & non-USA	non-OECD	non-OECD
Regression	Base	Wind	Base	Wind	Base	Wind
Ln Income per Capita	1.148**	1.636***	-0.624	-0.459	0.285***	0.229**
	(0.548)	(0.555)	(0.395)	(0.424)	(0.0986)	(0.0995)
Ln Population Density	-0.300	-0.342	0.298***	0.309**	0.0980	0.0677
	(0.266)	(0.284)	(0.0707)	(0.131)	(0.0869)	(0.0858)
Ln MSLP	-84.75***		-34.35**		-23.70***	
	(7.969)		(14.03)		(3.312)	
Ln Maximum Wind		5.069***		2.005		1.425***
		(0.622)		(1.450)		(0.239)
Ln Landfall Distance	-0.135	-0.0339	-0.690***	-0.680***	-0.351***	-0.322***
	(0.300)	(0.196)	(0.144)	(0.149)	(0.0427)	(0.0434)
Constant	592.1***	-17.07**	260.0***	13.88*	177.9***	9.737***
	(54.80)	(6.796)	(97.12)	(7.678)	(22.85)	(1.261)
Observations	108	110	95	81	653	652
R-squared	0.498	0.446	0.334	0.315	0.171	0.155

Note: *** p<0.01, ** p<0.05, * p<0.1.

IV. Conclusion

This paper develops a theory of adaptation to tropical cyclone damages and fatalities in order to test for the presence of adaptation. We add to the literature by constructing a new, larger, and more spatially-explicit historical dataset of more than 1,400 storms, matching cyclone landfall impacts with spatially-refined socioeconomic and cyclonic characteristics. A set of multiple regressions are then estimated with this new dataset to test for adaptation. Two types of tests are undertaken. First, we look at economic damage and explore whether the elasticity of income and to a lesser extent the elasticity of population density is unitary. We also look at fatalities and explore whether the elasticity of income is negative and whether the elasticity of population is less than unitary. We find clear evidence of adaptation in all of these tests. The damages and especially the fatalities are much less than one would expect if no adaptation measures were being undertaken.

We also use economic damage in the United States as a counterfactual. The subsidized flood insurance, state regulated private property insurance, and the generous emergency relief program combine to compensate victims of hurricanes handsomely in the United States. As a result, there is little private or local government incentive to adapt in the United States. Compensation mechanisms in the rest of the world are much smaller. Comparing the multiple regressions using just United States data, other OECD countries, and non-OECD countries reveals the United States has a unique damage function. The income elasticity of damage is unitary or higher, the elasticity with respect to intensity is much higher, and the constant is higher. If the United States had the damage function of the rest of the world, expected damages from hurricanes would be twenty times smaller. If the rest of the world had a damage function like the United States, damages would be twenty times higher. Adaptation to tropical cyclones is clearly very important.

Why is the United States an outlier? Although we leave precise mechanisms for future work, one major difference between the United States and the rest of the world is the role of public policy in shaping the incentives for coastal inhabitants to undertake risk. The incentive to adapt to tropical cyclones has been virtually eliminated in the United States. Coastal property is almost completely compensated for any risk from hurricanes by several policies. Many states limit how high insurance rates can climb for risky coastal areas effectively subsidizing high income households along the coast (Kousky, 2011). The National Flood Insurance Program charges insurance premiums that are well below what they must pay, especially when tropical cyclones strike. The U.S. Government Accountability Office finds that historical payouts exceed premiums by $30.4 billion (GAO, 2013). Post-disaster aid is funded through general tax revenues across the country instead of being paid by premiums (Krutilla, 1966; Kousky, 2010). The expectation of post disaster aid reduces adaptation (Kelly and Kleffner, 2003). All of these policies allow individuals to live in more risky areas and take few precautions to protect property. Some of the most rapidly developing areas in the United States are coastal, there is limited incentive to retreat to safer locations, and there is no incentive to invest in physical protection.

The research reveals adaptation to tropical cyclones is ongoing in most of the world and it is terribly important. However, the study does not provide critical details about this adaptation. How much of the adaptation is being done by private actors and how much by local and state governments? How much adaptation is in hard structures such as barriers and how much is just rational land use planning? What are the incentives to live by the sea relative to inland in the United States versus other countries? Very little is known about the distribution of damages within a tropical cyclone. How much of the damage is concentrated in low elevation sites along the shore? How much is due to storm surge, high winds, or fresh water flooding? More spatially detailed measures of storm characteristics, what is in harm's way, and damage are needed.

The research suggests several policy insights. We find that well-intentioned compensation of victims through public programs decreases the incentive to adapt. This applies to private individuals and firms as well as to local and state governments. This leads to over-capitalization in high risk areas that drive up aggregate observed damages and to the absence of adaptation measures. The public insurance programs in the United States need reform. Premiums need to cover the outlays for insurance to work properly. Fair insurance premiums provide a useful signal to households, firms, and farms informing them where risks are high and low. When policies prevent premiums from reflecting the true underlying risk, they eliminate this signal causing private individuals and firms to make poor choices. Although a national post disaster compensation program serves a valuable compassionate role, such programs can be paid for by assessing premiums on local and state governments consistent with long term payouts in each jurisdiction. Fair premiums provide a valuable incentive for governments to manage rather than ignore these risks.

Second, the results suggest that there may be room to improve the public communication of cyclone risks. Places with high intensity storms appear to have taken measures to reduce fatalities per storm. Yet fatalities per storm increase in places with many low intensity storms. It is unclear why fatalities are higher in places with more frequent low intensity storms. Researchers should explore whether public warnings can be improved to eliminate this effect. Fatalities have fallen over time in most countries again suggesting an effective adaptation program. However, the problem is not yet completely solved. For example, 77 percent of global fatalities occurred in just two countries, Myanmar and Bangladesh, over the last several decades[14]. It appears there are still some countries that can improve their overall performance.

Lastly, the results strongly suggest that economic development helps increase adaptation to natural disasters. The income elasticity of damage is less than one in every country except the United States. As countries develop, the damage from tropical cyclones will be a smaller component of their income. High income countries actually have lower aggregate damage. There is also strong evidence that per capita damage is much lower in urban areas. To the extent that development is both increasing incomes and urbanization, these factors will help reduce the future burden of storms on the economy. It is also quite clear that development is leading to fewer fatalities. Both urbanization and rising incomes is cutting fatalities rapidly. Development is a key component of adaptation to natural disasters.

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[14]Calculated by the authors using data from CRED (2012).

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Appendix For Online Publication

By Laura A. Bakkensen and Robert O. Mendelsohn*

This Online Appendix contains additional results and content mentioned in the paper.

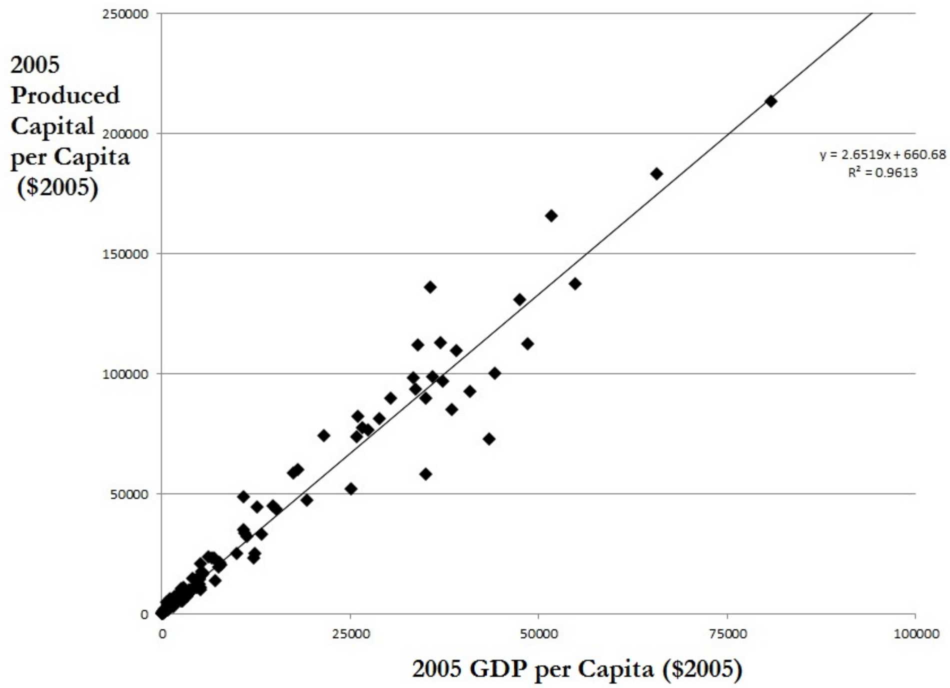
Capital Formation

Using the income approach, GDP can be calculated as the sum of all income generated by factors of production owned by people within a country (Gutierrez et al., 2007). Thus, GDP is equal to country population multiplied by the average income per capita. In Figure A1, we reproduce the work of Hallegate et al. (2013). Following Hallegate et al., we collect country-level 2005 data from the World Bank on GDP per capita from their World Development Indicators dataset, produced capital from World Bank staff estimates, and population compiled by the Wold Bank from several sources. Similar to Hansen (2011), they find a linear relationship between the capital stock and GDP per capita, although with a (per capita) capital to GDP ratio of 2.8 rather than 5. We find similar results to Hallegate et al., with a capital to GDP ratio of 2.65 and linear regression R^2 value of 0.96.

Additional empirical evidence also finds capital scaling proportionately with GDP. Using Organization of Economic Cooperation and Development data from Kamps (2004), in Figure A2 we plot forty-one years of capital stock as a percent of real GDP for twenty-two countries. Although the

* Yale University, 205 Prospect Street, New Haven, CT 06511, Laura.Bakkensen@yale.edu, Robert.Mendelsohn@yale.edu.

Figure A1. GDP per Capita and Capital per Capita Relationship



country-specific y-intercept is different, the within-country capital to GDP relationship remains strikingly linear over time. On average, the capital stock is 309 percent of annual GDP. The average within-country standard deviation was 23.5, or roughly 7.7 percent of the total capital to GDP ratio[1]. Thus, the empirical evidence supports the assumption that the capital stock scales proportionately with income and population. This observation is important for disaster impacts work, as it provides an upper bound on potential direct economic damages and also dictates how potential damages may change over varying levels of economic and population growth.

[1]These statistics were calculated by the author.

FIGURE A2. 1960-2001 COUNTRY CAPITAL STOCK AS A PERCENT OF REAL GDP (DATA FROM KAMPS, 2004)

Adaptation Framework

We first present the theoretical framework for why actors adapt. Both private and public adaptation occurs to minimize the sum of adaptation costs and expected damages. We explain how population and income shifts adaptation supply and demand, leading to changes in overall levels of protection. Lastly, we set up a simple model of the net impact of all adaptation measures on observed damages and fatalities. We generate empirically testable hypotheses of adaptation drivers including changes in income, population density, and the underlying frequency of storms, which we use as the foundation of our empirical strategy and results.

First, we set up the cost minimization problem. Assume each location, i, minimizes the sum of expected tropical cyclone damages and adaptation costs. Also assume that this location can be hit by two types of storms with different frequencies: low intensity tropical cyclones with characteristics TC_l and frequency Π_l, and high intensity tropical cyclones with characteristics TC_h with frequency Π_h, where $TC_l < TC_h$. Gross damages, GD, are a function of the tropical cyclone characteristics and the capital stock, K. Observed damages, D, are a function of gross damages and adaptation, A. We assume damages to be increasing in the magnitude of the storm, $\frac{dD}{dTC} > 0$, and the capital stock, $\frac{dD}{dK} > 0$. Adaptation occurs at a cost of $C(A)$, where $C(A)$ is assumed to be convex ($\frac{dC}{dA} > 0$ and $\frac{d^2C}{dA^2} > 0$). Adaptation is protective, $\frac{dD}{dA} < 0$, but at a declining rate, $\frac{d^2D}{dA^2} > 0$. Thus, the cost minimization problem can be written as the sum of expected damages plus costs:

$$\min_A \Pi_l D_l(TC_l, K, A) + \Pi_h D_h(TC_h, K, A) + C(A)$$

Assuming an interior solution[2], the location will adapt until the marginal cost of an additional unit of adaptation just equals the marginal benefit of damages avoided by that additional unit of adaptation:

$$\frac{dC}{dA} = \Pi_l \frac{dD_l}{dA} + \Pi_h \frac{dD_h}{dA}$$

Thus, as shown in Figure B1 below, adaptation works to decrease the observed damages from a cyclone landfalls. With no adaptation, observed damages would scale proportionally with the amount of capital at risk (see Hallegate et al., 2013). With adaptation, observed damages still increase as the capital stock increases, but at a smaller rate.

As shown in Figure B2, several factors influence the level of adaptation to damages by increasing the marginal benefit of adaptation. Increases in the level of capital stock from $Assets_1$ to $Assets_2$, where $Assets_1 < Assets_2$, and the frequency or strength of low and high intensity cyclones would all increase the level of adaptation through an outward shift in the marginal benefits curve. Ceteris paribus, this implies an increase in expected damages avoided from adaptation. Increases in the marginal costs of adaptation would decrease the level of adaptation while increases in units of protection undertaken would result in movement along the marginal benefit curve.

Similar to damages, a parallel relationship to protection and fatalities is constructed. Given no adaptation, observed fatalities would scale proportionally with the population in harm's way as seen in Figure B3. Changes in

[2]A corner solution is theoretically possible if the marginal adaptation cost and marginal damage functions do not intersect. This could occur because all adaptation is more costly than damages avoided, leading to no adaptation to damages suffered, or adaptation is less expensive per unit than the damages avoided, leading to full adaptation and the eradication of damages. Empirical evidence can confirm the interior solution assumption.

FIGURE B1. THE IMPACT OF ADAPTATION ON OBSERVED DAMAGES

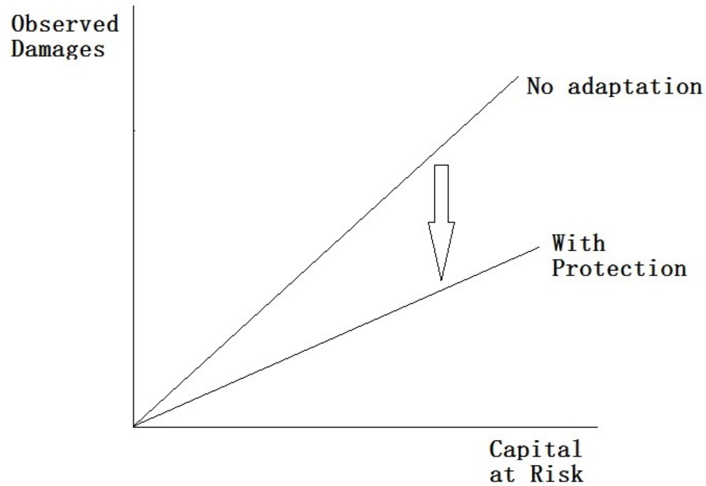
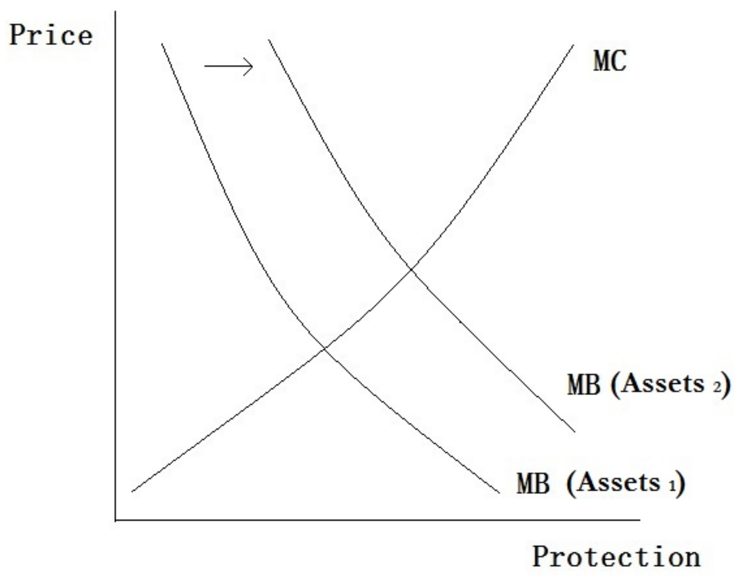
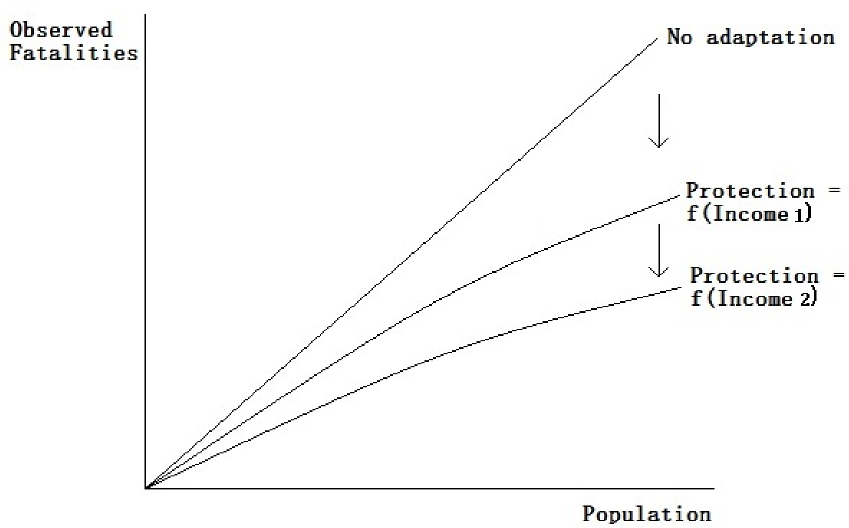


FIGURE B2. THE IMPACT OF INCOME ON THE LEVEL OF PROTECTION FROM DAMAGES



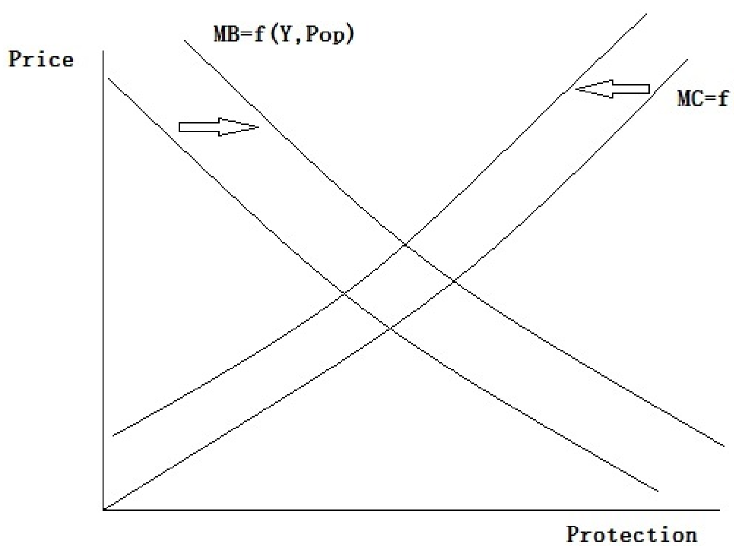
population would result in movement along the no adaptation frontier. For fatalities, adaptation may occur due to increases in income from $Income_1$ to $Income_2$, where $Income_1 < Income_2$, and also increases in the underlying probability of landfall. Both increase the marginal benefit of adaptation, as willingness to pay for protection against the risk of fatality is a normal good, thus as incomes increase, individuals pay more to adapt. Similarly, as the underlying frequency of landfalls increase, so does the expected marginal benefit of adaptation in terms of fatality avoided. Finally, Figure B4 depicts

Figure B3. The Impact of Adaptation on Observed Fatalities



the elements that shift the marginal cost and benefit of adaptation. First, increases in income and population lead to an outward shift in the marginal benefit curve, as higher income increases one's willingness to pay for protection, implying a higher value of statistical life. Additionally, increases in population will lead to higher marginal benefit of public adaptation efforts such as sea walls and evacuation programs. Thus, both factors lead to an outward shift in the marginal benefit curve. Lastly, population works in the opposite direction as well, by increasing the marginal cost of adaptation. This can be shown through evacuations. While effective at reducing the risk of fatality from storms, large-scale evacuation efforts can be costly due to factors such as additional fuel needed for retreat, additional hours spent on congested roads, and the potential for traffic accidents. Thus, the net impact of population on units of protection, and therefore observed damages, remains an empirical question.

Figure B4. The Impact of Income and Population on the Level of Protection from Fatalities



B1. Adaptation Mechanisms

Although this specific analysis calculates the net impact of a myriad of adaptation channels, there are many mechanisms through which adaptation could occur and these mechanisms may vary depending on the type of outcome in question. For fatalities, lives can be lost from storm surge, wind debris, and inland flooding. One major method to reduce deaths is advanced warning and evacuation systems, especially for high intensity storms. For lower intensity storms, taking shelter in a strong building away from the direct coastline is often sufficient, with basic supplies such as food, water, and other needs. Also, risks and costs of each adaptation method must be evaluated. For example, costs of evacuation (congestion, traffic accidents, disruption of care for hospital or elderly centers) may not outweigh the benefits of avoiding the storm path for some smaller storms. Turning to economic damages, adaptation methods are far-ranging. Fundamentally important are building strength and exterior reinforcements including sea walls and window shutters can all add levels of protection. There may be complementarity between adaptation to risk of fatalities and damages, as well. For example, a stronger house or a large sea wall can greatly reduce the risk of death from a lower category storm, and thus evacuation may be unnecessary. Lastly, adaptation may not be permanent. Some adaptation may have durable-good qualities and a very slow depreciation rate, such as a house built with stronger foundation and materials or a sea wall. Other types of adaptation, such as advanced notification and evacuation, will expire after the risk has passed and adaptation costs must be borne for each storm. This will impact optimal adaptation decisions.

B2. Maladaptation

Even though some degree of adaptation can be justified as a risk reduction strategy, other mechanisms are substitutes to adaptation that can increase damages, even in highly developed countries. Kelly and Kleffner (2003) show the optimal substitution between adaptation, insurance, and post disaster aid. They find that competitive insurance markets and the expectation of post disaster aid both reduce the amount of adaptation undertaken. Sadowski and Sutter (2005) find that, due to advancements in coastal warning systems, a decreased risk of fatality from living on the coast will increase the expected utility from coastal life. This leads to a net in-migration to coastal locations and an increase in cyclone damages. Also, some very low probability, high damage events may be prohibitively costly to adapt to, thereby increasing damages in locations who suffer these events (Hsiang and Narita, 2012; Kelly and Kleffner, 2003). However, the increase in damages during the late 1900s is most likely due to increased development and capital at risk and not due to climate change (Pielke, 2005; Pielke et al., 2008). Finally, there may be scope for public intervention to reduce damages if negative externalities occur in damages. For example, one building damaging another when portions of the first are blown away. In addition to adaptation, maladaptation may be in place if factors incentivize levels of adaptation that are below the efficient optimum. The optimal trade-off between levels of adaptation and substitutes is left for future work.

Discussion of Potential Concerns

In this section, we discuss potential concern of the study and try to persuade the reader that the concerns will not flaw the results.

C1. Measurement Error

Although EM-DAT has careful methods in place to collect and verify economic damage and fatality numbers, some measurement error may occur. With fatalities, reporting agencies must count the total number of lives lost and verification is usually possible and likely to occur. With damages data, no international accounting standard exists for reporting disaster damages and damages themselves may be hard to quantify. Thus, classical measurement error is a potential concern. But in the specifications contained in this analysis, data on deaths and fatalities are used exclusively as dependent variables, and thus no bias will occur in the estimated coefficients, although overall the regression will be more "noisy" with larger residual sum of squares. If there is instead strategic bias of reporting by countries, then bias could occur. For damages, if strategic reporting lead to an inflation of damage estimates by low income countries, perhaps for international aid, the bias would lead to an attenuation of the correlated coefficients to zero. If strategic reporting led to reduced damage records among low income countries, perhaps to draw attention away from disaster management, it would lead to an upward bias on estimated coefficients. To account for this, we also run subsample regressions partitioned on level of per capita income. Thus, strategic reporting will no longer be correlated with income and instead be absorbed by the constant term. It is unlikely that strategic misrepresentation of fatalities occurs, given the greater ability for external validation, but we also run sub-sample regressions based on income for these impacts as well.

Measurement error in an explanatory variable can bias the estimated coefficient (Wooldridge, 2010). However, measurement error in the dependent variable, uncorrelated with the explanatory variables will lead to no bias in the estimated parameters, only a noisy estimation due to a larger error term. Let us assume a linear function with dependent variable d and measurement error μ_D:

$$d + \mu_d = \hat{\beta}y + \epsilon$$

Assume that $E[y\epsilon] = 0$. The estimated β coefficient from the ordinary least squares estimator is derived as follows:

$$d + \mu_d = \hat{\beta}y + \epsilon$$

$$d + \mu_d - \hat{\beta}y = \epsilon$$

$$yd + \mu_d y - \hat{\beta}y'y = y\epsilon$$

$$E[yd] + E[\mu_d y] - E[\hat{\beta}y'y] = E[y\epsilon]$$

By assumption, $E[y\epsilon] = 0$

$$E[yd] + E[\mu_d y] - E[\hat{\beta}y'y] = 0$$

$$E[yd] + E[\mu_d y] = \hat{\beta}E[y'y]$$

$$\hat{\beta} = E[y'y]^{-1}(E[yd] + E[\mu_d y])$$

$$\hat{\beta} = E[y'y]^{-1}E[yd] + E[y'y]^{-1}E[\mu_d y]$$

Where $E[y'y]^{-1}E[yd]$ is the true β and $E[y'y]^{-1}E[\mu_d y]$ is any bias as a result of the measurement error. If the measurement error μ_d is uncorrelated (i.e., $E[\mu_d y] = 0$), then there is no bias in the estimator (i.e., $\hat{\beta} = \beta$).

Strategic Reporting

In the case of strategic reporting of cyclone damages, it is possible that the reporting error is not orthogonal to the explanatory variables (i.e., $E[\mu_d y] \neq 0$). In this case, one must think through the direction of correlation in order to ascertain the impact of the bias. In this cyclone example, it might be possible that countries that are net receivers of foreign aid (those with lower income per capita) may try to overstate their damage reports. Thus, $E[\mu_d y] < 0$ because for lower income per capita, y, they will have larger reported damages, μ_d. Thus, $0 < \hat{\beta} < \beta$, the estimated β coefficient suffers an attenuation bias and is closer to zero than the true β (Wooldridge, 2010). For the purposes of this analysis, it does not seem that there is much strategic reporting and the positive and statistically significant $\hat{\beta}$ is a good sign. Further, by performing sub-sample regressions partitioned on income, this strategic reporting would no longer be correlated with income and not bias the income coefficient results.

C2. Cyclone Frequency

Cyclones make good case studies as their year-to-year occurrences are basically random. Humans cannot do anything to generate, control the course, nor dissipate a tropical cyclone (HRD, 2013). Although cyclones have clearly defined long-term probabilities of occurring at any location, given the climate, their individual lives are as good as random. Even short term forecasting path and intensity has error (Emanuel, 2005). Thus, it is valid to assume that a cyclone landfall at a particular location is exogenous, although certainly individuals may adaptively react to upcoming cyclone threats. In addition to cyclone landings, human behavior impacts damages and fatalities. Notably, human location choice before and during a cyclone can potentially lead to endogeneity. But if this endogeneity is ex-ante adaptation to the storm, this is exactly what we want to capture in the analysis. The impact of this is unclear and will be left for future work. Currently, exogeneity is assumed.

C3. Cyclone Intensity

The definition of a cyclone already censors the sample, as a storm must have a maximum sustained 1-minute wind speed of above 64 knots for it to be classified as a hurricane by the U.S. National Hurricane Center. But censoring of the low-impact, low wind speed storms will likely not impact the results, as they are not the relevant range of interest. Note, too, that not all cyclones have both maximum wind speed and minimum sea level pressure readings. This is entirely due to agency rules over time[3] and is orthogonal to specific storm characteristics and locations (Knapp et al., 2010; IBTrACS personal communication, 2012).

We recommend further exploration of minimum sea level pressure as a proxy for cyclone intensity in place of maximum wind speed. It is possible that wind speed may be measured with greater error than minimum sea level pressure. Aircraft reconnaissance data can very accurately measure central pressure but wind speed estimates contain "considerable uncertainty" (Gray et al., 1991). Additionally, wind speed calculation techniques have changed over time without good documentation whereas minimum pressure reading techniques have remained consistent over time (Emanuel, 2013). Maximum

[3]For example, the Joint Tropical Warning Center reported only maximum wind speed until 2003 and the Japanese Meteorological Society reported minimum sea level pressure only until the mid-1990s.

wind speed is calculated differently throughout the world, with some calculated a 1-, 3-, or 10 minute sustained maximum wind speed. As there is no deterministic relationship between these sustained wind speeds, statistical averages must be used to convert them, leading records to divergence from the true values. Finally, historically some wind speed estimated have been derived statistically from pressure readings and heterogeneous advancements in technologies and statistical rules of thumb make it difficult to track the source of wind data (NRL, 1998). Thus, we recommend the use of minimum sea level pressure readings to be explored in future work.

C4. Endogeneity

We assume population and per capita income to be exogenous in this analysis. Some literature has looked at the endogeneity of these factors. Income per capita is not impacted greatly by an individual storm, except in very extraordinary cases. Storms making landfall at the same location is an infrequent occurrence. The literature on the impact of cyclones on gross domestic product growth is not conclusive and some even find positive impacts of cyclones on growth, depending on the time and geographic scale. More relevant to this research is the extent to which humans change their location choice (i.e. evacuate) when a cyclone approaches. It is assumed that most capital cannot be moved in the short run, only protected through adaptation.

C5. Multicollinearity

Independence between explanatory variables is a fundamental assumption of the Ordinary Least Squares estimator. If perfect correlation between explanatory variables exists, the matrix of explanatory variables will not

Table D1—Summary Statistics

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Damages (million $USD)	886	826	5,240	0.01	138,741
Fatalities (ppl/storm)	1062	393	6,051	1	138,866
Income per capita (PPP $USD)	1410	11,420	11,994	374	67,723
Real GDP per capita ($USD)	1410	8,246	11,753	34	76,208
Population density (ppl/km.sq.)	1410	448	1,526	0.01	33,922
Max. wind speed (kts)	1233	66	24	18	141
Min. sea-level pressure (mmbar)	1354	972	24	885	1,012
High intensity storm freq. (storms/yr)	1406	0.09	0.10	0	0.29
Low intensity storm freq. (storms/yr)	1406	1.57	1.34	0.001	3.60

satisfy the rank condition leaving it unable to invert. This does not occur in the present analysis. Highly correlated explanatory variables included in a regression will not bias the estimated coefficients. However, the correlation will lead to a"noisy" regression with larger standard errors and attenuation bias. Thus, the regression would tend to find a variable insignificant when, in reality, it is significant. One test for the impact of correlation is the Variance Inflation Factor (VIF). A score of more than 10 for any variable can indicate a multicollinearity problem. While the variables Low Count and High Count have a correlation of 0.71, neither have a VIF of greater than 10. Thus, multicollinearity is not likely to impact the significance of these variables.

Summary Statistics

The summary statistics for our data set are presented in Table D1.

Model Specification Checks

The specification of damages and fatalities functions are still debated in the literature. As such, care was taken to test multiple specifications and variables. Tables E1, E2, E5, and E6 are the results of these specification trials. The log-log functional form was chosen as the best fit.

E1. Alternative Variables

The literature commonly uses several variables in analyses, including maximum wind speed as a proxy for cyclone intensity and purchasing power parity (PPP) adjusted income per capita. We test several variables to find which were better predictors for cyclone fatalities and damages. The specifications for both fatalities and damages are as follows: column one is the base model with PPP income per capita, minimum sea level pressure (MSLP). Column 2 tests a quadratic specification in the income term. Column 3 introduces the market exchange rate real gross domestic product per capita from the USDA Macroeconomic panel dataset instead of PPP income per capita from the Penn World Table. Column 4 tests a quadratic term of real gdp per capita. Column 5 uses maximum wind speed instead of MSLP as a proxy for cyclone intensity, as opposed to Column 1. All specifications contain year fixed effects except for Column 6. Finally, all specifications contain the United States except for Column 7.

Table E1—Alternative Variables: Fatalities

VARIABLES	(1) Ln Fatalities	(2) Ln Fatalities	(3) Ln Fatalities	(4) Ln Fatalities	(5) Ln Fatalities	(6) Ln Fatalities	(7) Ln Fatalities
Ln Income per Capita	-0.618***	0.719			-0.611***	-0.651***	-0.669***
	(0.0868)	(1.285)			(0.0863)	(0.0886)	(0.0882)
Ln Income per Capita Squared		-0.0775					
		(0.0753)					
Ln Real GDP per Capita			-0.369***	0.257			
			(0.0714)	(0.870)			
Ln Real GDP per Capita Squared				-0.0388			
				(0.0527)			
Ln Population Density	0.145*	0.141	0.0444	0.0478	0.121	0.132*	0.155*
	(0.0870)	(0.0872)	(0.127)	(0.122)	(0.0910)	(0.0772)	(0.0857)
Ln Minimum Sea Level Pressure	-8.270***	-8.464***	-7.180**	-7.086**		-9.429***	-7.445**
	(2.905)	(2.790)	(3.113)	(3.066)		(2.791)	(2.904)
Ln Maximum Wind Speed					0.384**		
					(0.175)		
Ln Distance from Lanfall	-0.149***	-0.157***	-0.142***	-0.147***	-0.151***	-0.158***	-0.143***
	(0.0227)	(0.0210)	(0.0239)	(0.0228)	(0.0232)	(0.0227)	(0.0237)
Ln Low Count	0.279***	0.297***	0.233**	0.249**	0.273***	0.257**	0.287***
	(0.0996)	(0.103)	(0.116)	(0.120)	(0.0996)	(0.103)	(0.0999)
Ln High Count	-0.135**	-0.141**	-0.122	-0.127*	-0.131**	-0.118*	-0.146**
	(0.0653)	(0.0655)	(0.0764)	(0.0755)	(0.0643)	(0.0673)	(0.0661)
Constant	63.35***	58.91***	54.36**	51.22**	4.411***	70.86***	57.89***
	(20.49)	(20.69)	(21.73)	(20.97)	(0.946)	(19.67)	(20.61)
Year Fixed Effects?	Y	Y	Y	Y	Y	N	Y
USA Included?	Y	Y	Y	Y	Y	Y	N
Observations	1,006	1,006	1,006	1,006	995	1,006	950
R-squared	0.297	0.300	0.241	0.243	0.290	0.243	0.309

TABLE E2—ALTERNATIVE VARIABLES: DAMAGES

VARIABLES	(1) Ln Damages	(2) Ln Damages	(3) Ln Damages	(4) Ln Damages	(5) Ln Damages	(6) Ln Damages	(7) Ln Damages
Ln Income per Capita	0.403**	1.470			0.353**	0.420**	0.261
	(0.187)	(2.129)			(0.175)	(0.185)	(0.183)
Ln Income per Capita Squared		-0.0606					
		(0.130)					
Ln Real GDP per Capita			0.432***	-0.330			
			(0.0956)	(1.427)			
Ln Real GDP per Capita Squared				0.0458			
				(0.0886)			
Ln Population Density	0.0606	0.0580	0.137	0.139	-0.0342	0.0572	0.139
	(0.126)	(0.123)	(0.102)	(0.103)	(0.154)	(0.126)	(0.106)
Ln Minimum Sea Level Pressure	-28.40***	-28.29***	-29.14***	-29.18***		-29.94***	-24.22***
	(5.288)	(5.333)	(5.794)	(5.865)		(6.061)	(3.314)
Ln Maximum Wind Speed					1.738***		
					(0.412)		
Ln Distance from Lanfall	-0.393***	-0.398***	-0.390***	-0.384***	-0.349***	-0.413***	-0.390***
	(0.0523)	(0.0542)	(0.0529)	(0.0572)	(0.0560)	(0.0517)	(0.0585)
Ln Low Count	0.224	0.233	0.199	0.189	0.279**	0.169	0.180
	(0.139)	(0.141)	(0.138)	(0.141)	(0.139)	(0.140)	(0.136)
Ln High Count	-0.171*	-0.171*	-0.135	-0.136	-0.189*	-0.144	-0.173*
	(0.0900)	(0.0912)	(0.0903)	(0.0889)	(0.0957)	(0.0944)	(0.0878)
Constant	208.9***	203.5***	213.7***	217.1***	6.559**	219.3***	182.1***
	(35.44)	(41.90)	(39.18)	(43.24)	(2.928)	(41.31)	(23.48)
Year Fixed Effects?	Y	Y	Y	Y	Y	N	Y
USA Included?	Y	Y	Y	Y	Y	Y	N
Observations	844	844	844	844	832	844	736
R-squared	0.282	0.283	0.302	0.303	0.270	0.227	0.270

Statistical tests to guide specification are not conclusive. The Vuong test prefers the specification of Column 2 for fatalities, although with a p-value of 0.34 over Column 1 and a p-value of 0.81 over Column 7. The Vuong test prefers Column 7 for damages, with p-value of 0.20 over Column 3 and a p-value of 0.18 over Column 4. The AIC prefers the specification of Column 7 for fatalities and Column 5 for damages, while the BIC prefers Column 6 for fatalities and Column 7 for damages. See Burnham and Anderson (2004) for a comparison of the AIC and BIC tests.

For income, we try both PPP income per capita and market exchange rate gross domestic product per capita. For cyclone intensity, we examine both maximum wind speed and minimum sea level pressure at landfall. Table E1 summarizes the results for fatalities and Table E2 presents the results for damages. We find that PPP income per capita and minimum sea level pressure fit the best for fatalities, whereas the market exchange rate income per capita and minimum sea level pressure fit eh best for damages. But the magnitude of results stay consistent across specifications. Note that much of the literature uses maximum wind speed. This analysis, in additional to Mendelsohn et al. (2012), recommends that minimum sea level pressure be used.

E2. PDI and ACE

Lastly, we also include two additional variables to more fully characterize the underlying cyclone dynamics. We modify both the Power Dissipation Index (PDI; Emanuel, 2005c) and Accumulated Cyclone Energy index (ACE; Camargo and Sobel, 2005) and include it on our regressions. Both indexes integrate a power of the wind speed over the lifetime of the storm. As the lifetime of the storm over land is most relevant for cyclone impacts, we only intergrate over the lifetime of the storm over land. Thus, our modified PDI is defined as:

$$PDI = \sum_{I} \sum v^3$$

where v is the cubed velocity of the maximum sustained wind speed, in knots, summed for every six hour reading while over all land area of country of landfall I. Our modified ACE is defined as:

$$ACE = \sum_{I} v^2$$

which is identical to the PDI, except the wind velocity is squared instead of cubed. One potential issue with both indexes is that the final wind speed measurements over land may not be consistently recorded across agencies and over time. If the censoring occurs only at very low wind speeds, this will introduce only small amounts of measurement error in the calculation. To check this, we censor the data on our own at 34 knots, or the definition of a tropical storm. The results are included in Table E3 for fatalities and Table E4 for damages.

Note also that our sample size is smaller with the ACE and PDI regressions. This is because only roughly 64 percent of cyclones make direct landfall. Thus, the elasticities are interpreted a local average treatment effect. For both tables, Column 1 presents the base results of the regressions on the smaller sample size. Columns 2 and 3 introduce the PDI and PDI 34, respectively. Columns 4 and 5 introduce the ACE and ACE 34, respectively. We estimated the regressions using Ordinary Least Squares

Table E3—PDI and ACE: Fatalities

VARIABLES	(1) Ln Fatalities	(2) Ln Fatalities	(3) Ln Fatalities	(4) Ln Fatalities	(5) Ln Fatalities
Ln Income PC	-0.556***	-0.553***	-0.530***	-0.537***	-0.532***
	(0.0900)	(0.0989)	(0.0990)	(0.0940)	(0.0982)
Ln Pop Density	0.253***	0.274***	0.268***	0.233***	0.272***
	(0.0469)	(0.0656)	(0.0735)	(0.0539)	(0.0740)
Ln MSLP	-15.20***	-9.327***	-10.69**	-13.99***	-11.06***
	(2.143)	(3.439)	(4.019)	(2.915)	(3.561)
Ln Distance	-0.280***	-0.292***	-0.326***	-0.295***	-0.318***
	(0.0827)	(0.0897)	(0.101)	(0.0862)	(0.102)
Ln Low Count	0.275**	0.258*	0.287*	0.239	0.281*
	(0.122)	(0.150)	(0.154)	(0.144)	(0.154)
Ln High Count	-0.109	-0.117	-0.109	-0.101	-0.110
	(0.0726)	(0.0903)	(0.0945)	(0.0881)	(0.0953)
Ln PDI		0.215**			
		(0.0907)			
Ln PDI 34			0.198*		
			(0.107)		
Ln ACE				0.0987	
				(0.0924)	
Ln ACE 34					0.272**
					(0.121)
Constant	109.0***	66.01***	75.02**	100.1***	77.76***
	(14.58)	(24.29)	(28.62)	(20.29)	(25.11)
Observations	559	470	437	476	437
R-squared	0.239	0.243	0.238	0.242	0.241

Table E4—PDI and ACE: Damages

VARIABLES	(1) Ln Damages	(2) Ln Damages	(3) Ln Damages	(4) Ln Damages	(5) Ln Damages
Ln Income PC	0.855***	0.773***	0.791***	0.805***	0.791***
	(0.237)	(0.244)	(0.254)	(0.227)	(0.245)
Ln Pop Density	0.269***	0.201**	0.197*	0.154*	0.210*
	(0.0846)	(0.0998)	(0.109)	(0.0795)	(0.107)
Ln MSLP	-28.24***	-15.29*	-15.48*	-23.61***	-17.10**
	(5.281)	(8.181)	(8.888)	(5.697)	(7.677)
Ln Distance	-0.485**	-0.460**	-0.412**	-0.420**	-0.391*
	(0.191)	(0.193)	(0.198)	(0.193)	(0.200)
Ln Low Count	0.174	0.384	0.420	0.313	0.395
	(0.279)	(0.281)	(0.283)	(0.274)	(0.274)
Ln High Count	-0.0217	-0.132	-0.116	-0.0875	-0.114
	(0.188)	(0.192)	(0.191)	(0.187)	(0.186)
Ln PDI		0.501***			
		(0.172)			
Ln PDI 34			0.537***		
			(0.200)		
Ln ACE				0.289*	
				(0.167)	
Ln ACE 34					0.711***
					(0.226)
Constant	202.2***	106.4*	106.5*	167.8***	118.5**
	(36.85)	(57.87)	(63.44)	(40.04)	(54.48)
Observations	455	389	373	398	373
R-squared	0.265	0.273	0.271	0.270	0.278

estimated. Standard errors are clustered at the country level.

There are several important conclusions. First, the PDI and ACE are both statistically significant and their signs are as expected. A storm with higher accumulated energy and power is positively correlated with fatalities and damages. Also important is that there is minimal change in the estimated socioeconomic elasticities. This implies that, while the PDI and ACE are important variables to include, omission of the variables will not result in omitted variable bias for socioeconomic factors. One note, however, is that the PDI and ACE only characterize the storm characteristics and not the underlying human communities affected. Both are important in determining damages, therefore a better variable would interact and index the storm power with levels relevant human development. Overall, we find that the ACE and PDI are relevant cyclone characteristics to be included in future analyses.

E3. Functional Form

In addition to variable tests, we test various functional form specifications using income per capita adjusted by purchasing power parity in Table E5 for fatalities and E6 for damages. In both Tables, we test a linear specification for all variables in Column 1. Column 2 logs the dependent variable for a log-linear specification. Column 3 introduces a squared term for income per capita. Column 4 introduces a cubic term for income per capita. Column 5 takes the natural log of all variables and includes only income per capita with no higher order terms. Column 6 includes a quadratic term for per capita income. The specification tests are more consistent, preferring Columns 5 and 6. The Vuong test prefers Column 6 for both damages and fatalities, but only weakly over Column 5 with a p-value of 0.55 for fatalities and 0.68 for damages. Both the AIC and BIC tests prefer Column 5 for both damages and fatalities.

The fatalities results are presented in Table E5. The linear specification in Column 1 is the poorest performing, as minimum sea level pressure, key in controlling for the intensity of the storm, lacks significance. Log-linear specifications in Columns 2 through 4 fair better and estimated coefficients remain fairly constant across the linear, quadratic, and cubic per capita income proxies. Ultimately, the log-log specification was chosen as it had the greatest coefficient of determination with the fewest number of variables. A squared log income per capita term was also tested, but both per capita terms terms lost significant. Thus, it is possible that the log-log form best fits the data among these functional forms, and the log-linear forms attempt to replicate the constant income elasticity in their shapes. Finally, the fact that all estimated coefficient signs are in the expected directions also adds confidence in the analysis.

Table E5—Functional Form: Fatalities

VARIABLES	(1) Fatalities	(2) Ln Fatalities	(3) Ln Fatalities	(4) Ln Fatalities	(5) Ln Fatalities	(6) Ln Fatalities
Income per Capita	-0.0372*	-4.77e-05***	-0.000115***	-0.000192***		
	(0.0215)	(5.25e-06)	(1.21e-05)	(2.61e-05)		
Income per Capita Squared			1.75e-09***	5.86e-09***		
			(2.69e-10)	(1.23e-09)		
Income per Capita Cubed				-0***		
				(0)		
Ln Income per Capita					-0.573***	0.242
					(0.0472)	(0.711)
Ln Income per Capita Squared						-0.0472
						(0.0409)
Population Density	0.0442	-6.27e-08	1.33e-05	1.27e-05		
	(0.0508)	(2.95e-05)	(2.60e-05)	(2.64e-05)		
Ln Population Density					0.181***	0.181***
					(0.0333)	(0.0333)
Minimum Sea Level Pressure	-21.64	-0.00866***	-0.00884***	-0.00841***		
	(15.25)	(0.00261)	(0.00256)	(0.00254)		
Ln Minimum Sea Level Pressure					-8.486***	-8.657***
					(2.319)	(2.321)
Landfall Distance	-0.493*	-0.000898***	-0.000876***	-0.000832***		
	(0.299)	(0.000252)	(0.000252)	(0.000252)		
Ln Landfall Distance					-0.179***	-0.186***
					(0.0213)	(0.0220)
Constant	21,381	13.09***	13.44***	13.17***	66.45***	64.21***
	(14,963)	(2.557)	(2.513)	(2.491)	(16.02)	(16.21)
Observations	1,020	1,020	1,020	1,020	1,020	1,020
R-squared	0.036	0.191	0.216	0.224	0.283	0.284

TABLE E6—FUNCTIONAL FORM: DAMAGES

Variables	(1) Damages	(2) Ln Damages	(3) Ln Damages	(4) Ln Damages	(5) Ln Damages	(6) Ln Damages
Income per Capita	77,119***	4.34e-05***	5.89e-05***	0.000134***		
	(28,278)	(7.94e-06)	(2.28e-05)	(4.93e-05)		
Income per Capita Squared			-3.81e-10	-4.16e-09*		
			(5.59e-10)	(2.40e-09)		
Income per Capita Cubed				0		
				(0)		
Ln Income per Capita					0.440***	1.494
					(0.0788)	(1.300)
Ln Income per Capita Squared						-0.0599
						(0.0742)
Population Density	-41,562	-2.76e-05	-3.01e-05	-3.04e-05		
	(45,407)	(6.46e-05)	(6.54e-05)	(6.29e-05)		
Ln Population Density					0.0791	0.0778
					(0.0583)	(0.0581)
Minimum Sea Level Pressure	-3.142e+07*	-0.0298***	-0.0296***	-0.0295***		
	(1.695e+07)	(0.00354)	(0.00355)	(0.00353)		
Ln Minimum Sea Level Pressure					-28.17***	-28.12***
					(3.332)	(3.336)
Landfall Distance	-367,525	-0.00155**	-0.00156**	-0.00162**		
	(234,435)	(0.000642)	(0.000642)	(0.000649)		
Ln Landfall Distance					-0.381***	-0.389***
					(0.0428)	(0.0438)
Constant	3.058e+10*	46.78***	46.56***	46.24***	208.1***	203.2***
	(1.631e+10)	(3.584)	(3.599)	(3.596)	(23.02)	(23.95)
Observations	856	856	856	856	856	856
R-squared	0.095	0.211	0.211	0.215	0.274	0.274

Similar to the fatalities functions, we test several specifications of a damages function. Results are presented in Table E6, with standard errors clustered at the country level. The linear specification of Column 1 is again the poorest performing, as minimum sea level pressure and the constant are both insignificant. It also has a very low coefficient of determination. Log-linear specifications in Columns 2 through 4 improve upon the linear specification, but the squared and cubic terms have weak or no significance in Columns 3 and 4. Again, the log-log specification of Column 5 was chosen for its parsimony and power. Including a squared income per capita term did not improve the specification. Again, the fact that all estimated coefficient signs are in the expected directions also adds confidence in the analysis. It seems that the estimated coefficient of population density is consistently statistically similar to zero.

Negative Binomial Regression Results

In this section, we present the results of the negative binomial estimator. The negative binomial estimator, a count data technique, is advantageous to OLS if regression outcomes are discrete, countable, and not normally distributed. We already introduce nonlinearity and non-normality in the OLS specification due to the log-log functional form. Thus, neither estimator is necessarily superior. We use the negative binomial estimator instead of the poisson regression due to over-dispersion in the fatalities data. The alpha statistic is equal to 2.2 with a standard error of 0.14, so the data are over-dispersed and the negative binomial is preferred to the poisson regression.

In Table F1 below, we present the results for a regression of all countries in the globe. Column 1 includes a year fixed effect. Column 2 includes year and time fixed effects. Columns 1 and 2 use the same specifications as columns in the main paper, except with a negative binomial estimator instead of ordinary least squares. We find similar results for the negative binomial results as with the cross sectional and panel data techniques, with income growth decreasing fatalities in the first specification, with an estimated elasticity of -0.879. Column 2 reports a positive estimated income elasticity of fatality, which is not seen in any other specification. Greene (2007) caution the use of fixed effects in negative binomial regressions, so the results should be taken carefully until the debate is resolved. All other coefficient signs are as expected, including a positive but less than one estimated elasticity on the population density term, a negative and statistically significant pressure elasticity, and the dichotomous relationship between low and high intensity storm elasticities. Thus, evidence of warning fatigue is present also in the negative binomial specifications.

Table F2 reports results of the negative binomial regression for low income and high income locations with less than $6,500 income in Column 1 and more than $20,000 income per capita in Column 2. These specifications pattern those in the main paper with cross-sectional and panel data techniques. Both specifications contain only year fixed effects. Again, the signs and relative magnitudes are as expected. We find that the income elasticities of low and high income locations are negative and the magnitude of the elasticity is more negative in high income locations, relative to low income locations, showing an increase in adaptation, perhaps due to an increase in public adaptation, as incomes increase.

Thus, we find similar results between the cross-sectional, panel, and count

Table F1—Negative Binomial Regression with Fixed Effects: Evidence of Adaptation to Fatalities

VARIABLES	(1) Fatalities	(2) Fatalities
Ln Income Per Capita (Y)	-0.879***	0.0602*
	(0.109)	(0.0352)
Ln Population Density (Pop)	0.222**	0.0250
	(0.0972)	(0.0263)
Ln Intensity (TC_x Pressure)	-16.81***	-4.533***
	(3.975)	(1.321)
Ln Frequency Low (Π_L)	0.216*	0.183***
	(0.115)	(0.0625)
Ln Frequency High (Π_H)	-0.192***	-0.148***
	(0.0576)	(0.0366)
Ln Landfall Distance (L)	-0.164***	-0.0531***
	(0.0274)	(0.0145)
Constant	125.7***	29.81***
	(28.02)	(0.0643)
Year FE	Y	Y
Country FE	N	Y
Observations	1,006	994

Table F2—Negative Binomial Regression with Year Fixed Effects: Low and High Income Locations Fatalities

	(1)	(2)
Income Level	<\$6,500	>\$20,000
VARIABLES	Fatalities	Fatalities
Ln Income Per Capita (Y)	-0.445	-3.025***
	(0.389)	(0.650)
Ln Population Density (Pop)	0.0856	0.244**
	(0.288)	(0.104)
Ln Intensity (TC_x Pressure)	-22.31**	-20.84***
	(8.983)	(6.712)
Ln Landfall Distance (L)	-0.254**	-0.163***
	(0.107)	(0.0634)
Constant	162.5**	175.7***
	(64.40)	(47.93)
Observations	579	152

data regression techniques presented in this paper. This gives us confidence in the qualitative results of our study.

Elasticities Across Income Levels

In Figures G1 and G2, we graph the results of income elasticities in segmented bins from low to high income countries with a quadratic trend line imposed. All regressions include country and decade fixed effects and have standard errors clustered at the country level. Table G1 defines the income bins in Figures G1 and G2. To check the validity of the clustered standard errors in the bins with fewer than fifty bins, we employ wild bootstrapping as described by Cameron et al. (2008) and implemented in Stata with Caskey (2013).

Table G1—Income Elasticities Bin Key for Figures G1 and G2

Number	Income Bin
1	<$2,500
2	<$5,000
3	<$10,000
4	$2,500 to $15,000
5	$5,000 to $17,500
6	$7,500 to $25,000
7	$10,000 to $30,000
8	$12,500 to $32,500
9	$15,000 to $35,000
10	$17,500 to $37,500
11	$20,000 to $40,000
12	$22,500 to $42,500
13	$25,000 to $45,000

FIGURE G1. INCOME ELASTICITIES OF FATALITIES ACROSS INCOME LEVELS

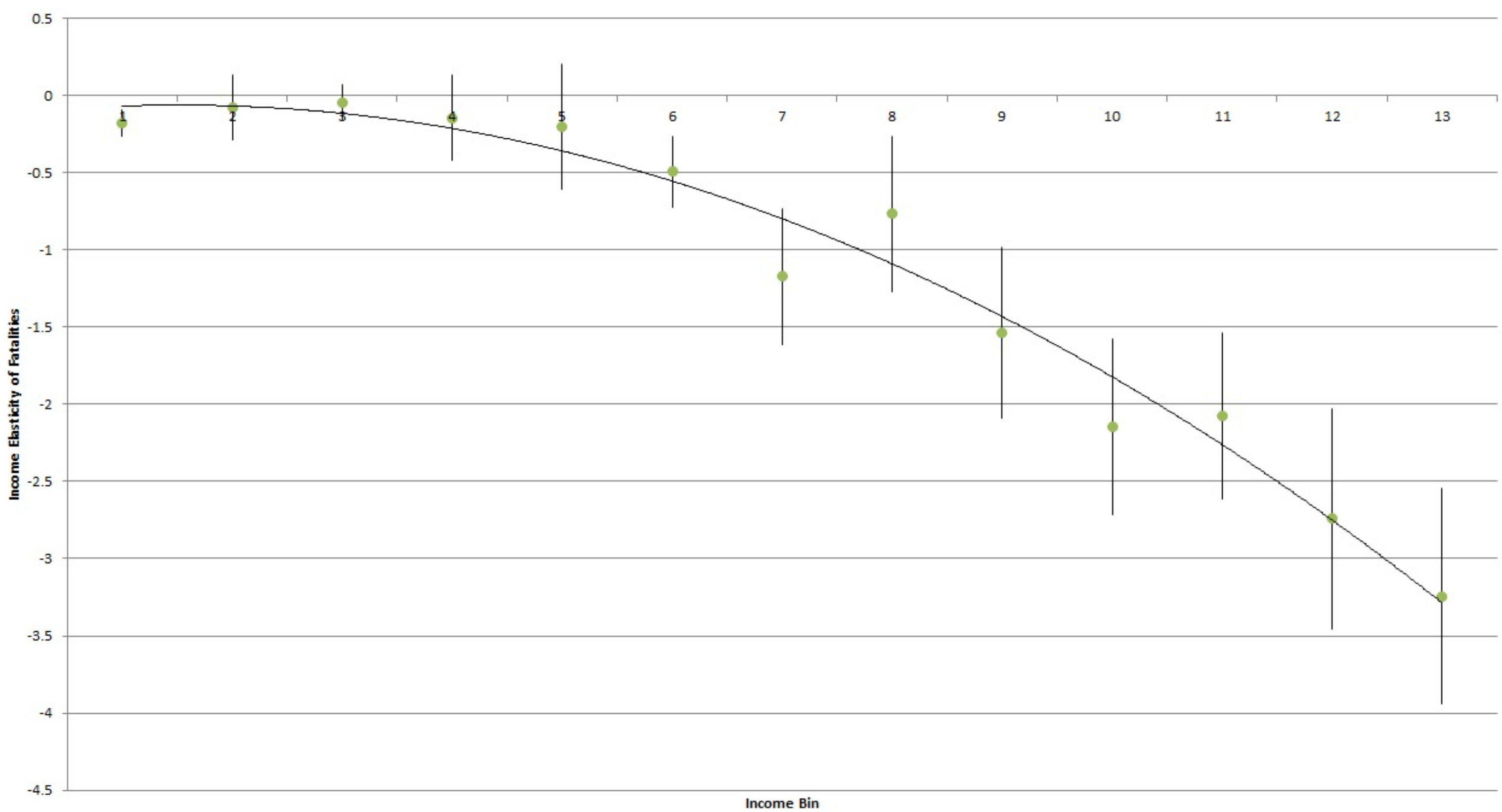
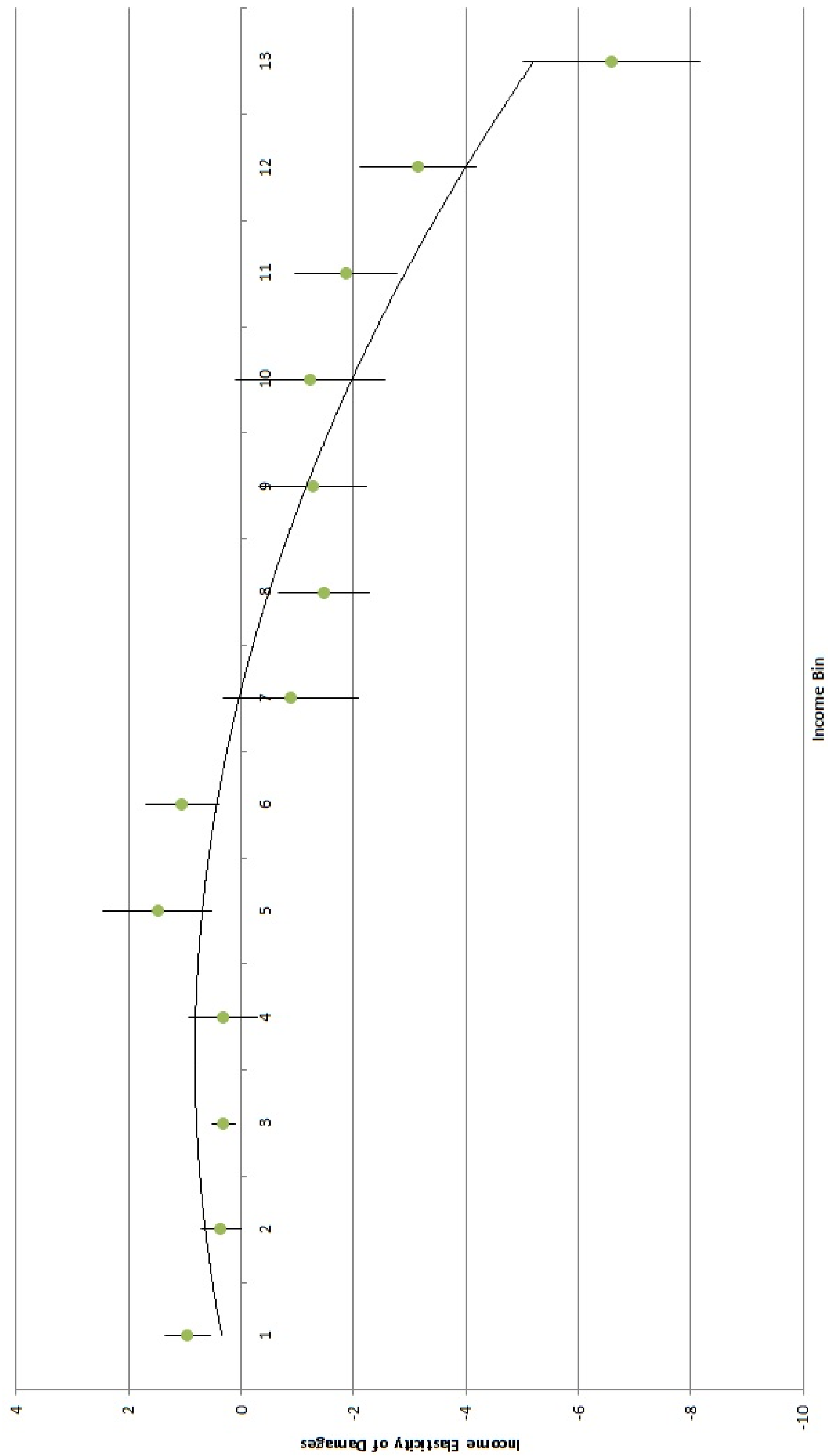


Figure G2. Income Elasticities of Damages across Income Levels



In Tables G2 and G3 below we present tables of the regressions underlying Figures G1 and G2. The regression are segmented by level of income per capita with a sliding bin ranging from less than $2,500 to more than $25,000. Explicit bin values are labeled in the Income Range row. Each specification has decade and country fixed effects and standard errors are clustered at the country level. Due to the presence of few clusters in some of the high income country bins, we also employ a wild bootstrapping technique (Cameron et al., 2008; as implemented by Caskey, 2013) and test the hypothesis that each coefficient is different from zero.

We find that development unequivocally reduces fatality risk. Countries trend monotonically to lower income elasticities of fatalities as they develop, with income elasticities approximately zero for the least developed nations and between -2 and -3 for the highest income locales. For very developed nations, these very low income elasticities of fatalities are higher than what can be explained solely by increases in the private value of statistical life. Thus, they are likely evidence of public adaptation to fatalities.

Development also impacts the income elasticity of damages, although with a more noisy shape to the relationship. The income elasticity of damages has a tension with development. Development can increase damages by the scale effect increasing the amount of capital stock at risk, thereby increasing the total potential damages. On the other hand, development can also increase funds available for adaptation. In this sense, development could increase or decrease cyclone damages. Income elasticity of damages appear to be hill-shaped, first increasing slightly and then decreasing, with statistically different income elasticities between high and low income countries. For very low income locations with income per capita of less than $5,000, the scale effect dominates the adaptation effect, leading to an income elasticity of development no different from one. But as countries develop, the adaptation effect greatly outweighs the scale effect, leading to income elasticities significantly below zero. For the highest income countries, these income elasticities are less than -1.8. Thus, we find development beneficial to adaptation for fatalities. Development also protects against damages, although the scale effect outweighs the adaptation effect at low levels of development.

Table G2—Income Elasticities of Fatalities across Income Levels

VARIABLES	(1) Ln Fatalities	(2) Ln Fatalities	(3) Ln Fatalities	(4) Ln Fatalities	(5) Ln Fatalities	(6) Ln Fatalities	(7) Ln Fatalities	(8) Ln Fatalities	(9) Ln Fatalities	(10) Ln Fatalities	(11) Ln Fatalities
Ln Income per Capita	-0.0413	-0.142	-0.202	-0.491**	-1.172**	-0.765	-1.534**	-2.146***	-2.076***	-2.741***	-3.244***
	(0.111)	(0.281)	(0.405)	(0.231)	(0.441)	(0.504)	(0.554)	(0.572)	(0.539)	(0.715)	(0.697)
Ln Population Density	0.231*	0.267**	0.285**	0.182***	0.201*	0.270*	0.165**	0.195***	0.199***	0.175***	0.127
	(0.136)	(0.104)	(0.107)	(0.0602)	(0.111)	(0.152)	(0.0777)	(0.0554)	(0.0585)	(0.0453)	(0.0741)
Ln MSLP	-11.53***	-7.668***	-2.863	-7.165**	-5.229	-7.072	-2.247	0.462	-2.091	-3.139	0.290
	(2.317)	(2.313)	(4.460)	(3.448)	(3.794)	(4.574)	(2.892)	(2.786)	(2.925)	(3.989)	(4.149)
Ln Maximum Wind Speed	-0.161***	-0.152***	-0.132***	-0.144***	-0.123***	-0.156**	-0.166***	-0.153***	-0.166***	-0.165**	-0.000842
	(0.0214)	(0.0295)	(0.0325)	(0.0400)	(0.0434)	(0.0638)	(0.0587)	(0.0454)	(0.0480)	(0.0575)	(0.0866)
Ln Landfall Distance	83.30***	57.01***	24.02	56.43**	48.77*	58.24*	32.68	20.10	37.25	50.92*	32.87
	(16.55)	(16.68)	(30.72)	(24.06)	(25.24)	(31.05)	(20.52)	(19.62)	(22.67)	(27.12)	(33.17)
Income Range	<$10,000	$2,500 to 15000	$5,000 to $17,500	$7,500 to $25,000	$10,000 to $30,000	$12,500 to $32,500	$15,000 to $35,000	$17,500 to $37,500	$20,000 to $40,000	$22,500 to 42500	>$25000
Observations	684	465	282	257	241	199	186	162	146	126	94
R-squared	0.185	0.197	0.164	0.240	0.146	0.147	0.140	0.124	0.125	0.157	0.086
Number of Countries	66	58	49	40	34	25	24	21	20	18	14

TABLE G3—INCOME ELASTICITIES OF DAMAGES ACROSS INCOME LEVELS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
VARIABLES	Ln Damages	Ln Damages	Ln Damages	Ln Damages	Ln Damages	Ln Damages	Ln Damages	Ln Damages	Ln Damages	Ln Damages	Ln Damages	Ln Damages	Ln Damages
Ln Income per Capita	0.948**	0.356	0.311	0.312	1.477	1.044	-0.887	-1.475*	-1.289	-1.237	-1.871*	-3.150***	-6.601***
	(0.400)	(0.349)	(0.213)	(0.616)	(0.972)	(0.659)	(1.206)	(0.818)	(0.958)	(1.323)	(0.907)	(1.031)	(1.571)
Ln Population Density	-0.511***	-0.0321	0.0119	0.328***	0.0661	0.210***	0.426***	0.512***	0.412***	0.398***	0.452***	0.535**	0.746**
	(0.0635)	(0.0687)	(0.0583)	(0.0972)	(0.186)	(0.0405)	(0.0804)	(0.0622)	(0.0573)	(0.0936)	(0.149)	(0.197)	(0.272)
Ln MSLP	-26.73***	-25.19***	-23.11***	-20.31***	-16.37**	-25.18***	-32.27***	-34.38***	-35.79***	-39.37***	-36.59***	-41.93***	-32.14**
	(4.533)	(2.353)	(3.118)	(4.330)	(7.879)	(6.742)	(5.324)	(6.399)	(6.897)	(11.00)	(9.506)	(10.01)	(11.27)
Ln Landfall Distance	-0.432***	-0.399***	-0.373***	-0.338***	-0.347**	-0.431***	-0.432***	-0.564***	-0.530***	-0.543***	-0.659***	-0.637***	-0.248
	(0.134)	(0.0621)	(0.0636)	(0.0668)	(0.133)	(0.152)	(0.107)	(0.112)	(0.115)	(0.123)	(0.117)	(0.127)	(0.208)
Constant	198.6***	189.5***	175.1***	154.2***	118.4**	182.3***	248.8***	269.5***	275.0***	299.3***	286.6***	335.4***	302.5***
	(30.83)	(15.88)	(22.12)	(31.33)	(55.25)	(47.54)	(39.48)	(43.98)	(44.96)	(73.76)	(64.56)	(69.59)	(68.88)
Income Range	<$2,500	<$5,000	<$10,000	$2,500 to 15000	$5,000 to $17,500	$7,500 to $25,000	$10,000 to $30,000	$12,500 to $32,500	$15,000 to $35,000	$17,500 to $37,500	$20,000 to $40,000	$22,500 to $42500	$25000 to $45000
Observations	184	355	502	376	232	215	206	181	173	151	138	121	92
R-squared	0.218	0.231	0.187	0.173	0.129	0.168	0.209	0.264	0.223	0.207	0.252	0.239	0.176
Number of Countries	18	38	60	57	49	39	34	27	27	22	22	20	17

Future work will continue to investigate factors impacting adaptation decisions, as many questions still remain surrounding the mechanisms underlying adaptation decisions and the external validity of tropical cyclone work to natural disasters at large. Understanding explicit measures of adaptation is an important next step. Additionally, more work is needed in impact analyses, including more spatially detailed impacts and differentiating between damages from wind versus water. Lastly, improved international accounting of disaster damages is greatly needed to better understand impacts and adaptation.

Fatalities in the United States

Table H1 presents the results for fatality subsample regressions. Columns 1 and 2 are for the United States, Columns 3 and 4 include OECD countries (excluding the United States), and Columns 5 and 6 include non-OECD countries.

TABLE H1—UNITED STATES FATALITIES

	(1)	(2)	(3)	(4)	(5)	(6)
Countries	USA	USA	OECD & non-USA	OECD & non-USA	non-OECD	non-OECD
VARIABLES	Ln Fatalities	Ln Fatalities	Ln Fatalities	Ln Fatalities	Ln Fatalities	Ln Fatalities
Ln Income per Capita	-0.538	-0.609	-1.701***	-1.715***	-0.758***	-0.743***
	(0.406)	(0.401)	(0.228)	(0.229)	(0.0554)	(0.0572)
Ln Population Density	0.242**	0.285**	0.273***	0.273***	0.159***	0.107***
	(0.101)	(0.111)	(0.0583)	(0.0490)	(0.0391)	(0.0411)
Ln MSLP	-23.28***		-3.003		-9.047***	
	(8.553)		(5.520)		(2.396)	
Ln Maximum Wind		1.574***		-0.0774		0.511***
		(0.563)		(0.352)		(0.138)
Ln Landfall Distance	-0.246**	-0.235***	-0.142***	-0.144***	-0.187***	-0.187***
	(0.0927)	(0.0815)	(0.0502)	(0.0541)	(0.0228)	(0.0232)
Constant	167.2***	1.007	38.91	18.75***	70.90***	6.746***
	(58.24)	(5.265)	(38.63)	(2.610)	(16.55)	(0.689)
Observations	56	58	116	108	848	842
R-squared	0.320	0.317	0.466	0.485	0.247	0.232

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.