Risk and Adaptation: Evidence from Global Hurricane Damages and Fatalities

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Abstract

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)

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Economists are well aware that people and firms adapt to risk. People use smoke detectors for protection from residential fire (Dardis, 1980), seat belts for protection from traffic accidents (Atkinson and Halvorsen, 1990), and sunscreen for protection from ultraviolet rays (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 often normalizes impacts. This implies that damage is proportional to what is in harm's way and increases proportionally with country-level 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. This also implies that adaptation is not effective in reducing damages. The literature is more ambiguous about fatalities, as there has long been evidence of adaptation. However studies normalize fatalities, assuming fatality increases proportionately with national 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 income elasticity of 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. We also calculate additional socioeconomic and cyclone elasticities of impacts and compare with theoretical thresholds to test for additional types of 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 sixty percent 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 by a combination of subsidized national flood insurance, state regulations on coastal property insurance rates, and generous post disaster relief programs. Households, 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 inten-

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

sity, 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. This represents the complete set of storms for which damage and fatality impacts are publicly available[2]. 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 underlying frequency of low and high intensity storm landfalls for each area and explore to what degree prior experience affects the impacts per storm.

We are not the first to tackle the question of adaptation. Several papers find evidence of adaptation in response to development and institutions (Kahn, 2005; Toya and Skidmore, 2007; Kellenberg and Mobarak, 2007; Fankhauser and McDermott, 2013), as well as the underlying risk of disaster (Keefer, Neumayer, and Plumper, 2011; Schumacher and Stobel, 2011; Hsiang and Narita, 2012). Additionally, a rich literature examines the im-

[2]Hsiang and Jina (2014) note there are 6,700 storms in recorded history after 1950. However, many do not make landfall and fewer still have records of damage and fatality impacts. We collect the complete set of storms that have publicly-available recorded impacts.

pact of hurricanes on long-run economic growth (Skidmore and Toya, 2002; Strobl, 2011; Cavallo et al., 2013; Hsiang and Jina, 2014). Cavallo and Noy (2010) and Kousky (2012) provide informative review papers. Similar to the existing literature, we only identify the benefits of adaptation and not the costs or net benefits. However, previous literature has shown that at current levels of adaptation, benefits likely far exceed costs in coastal areas (Yohe, Neumann, and Ameden, 1995; Ng and Mendelsohn, 2005). Other studies on hurricane effects include Hallstrom and Smith (2005) and Smith et al. (2006).

We build upon this important work in several original ways. First, we offer a comprehensive framework to approach the question of adaptation, extending to both damages and fatalities and covering multiple channels through which adaptation is motivated (including level of development, population density, storm characteristics, and underlying risk of storm landfalls). Second, we collect the most spatially-refined global dataset to date. We include socioeconomic data at the sub-country level and use a unit of observation at the country-landfall, not country-year. This allows us to directly model damages and fatalities per storm, instead of modeling aggregated annual values. It also insures that any missing data are excluded from the analysis instead of assumed to be zero. Third, we find clear evidence that adaptation matters and quantify the reduction in damages from adaptation. Unlike previous work that finds adaptation only reduces long run damages and fatalities by around 3 percent (Hsiang and Narita, 2012), we find it is greatly protective and reduces impacts by more than an order of magnitude.

We find ample evidence of the benefits 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 per storm. If the United States had the same damage coefficients as the rest of the world, the expected annual American damage from hurricanes would be $0.8 billion instead of the observed $15.3 billion. If the rest of the world had the same damage coefficients as the United States, non-US global damage would be $208 billion per year instead of the observed $10.4 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.

1 Theory

Faced with a set of risks, individuals and governments often take steps to protect themselves. We define adaptation broadly, as any action that reduces the expected damages or fatalities from a storm. Broad-scale improvements in forecasting and tracking as well as advanced warning systems are included as adaptation. Large infrastructural development in flood protection including levees, river channelization, and beach nourishment are included. Further, improvements in building codes, zoning ordinances, or individual activities to strengthen homes, including hurricane shudders and stronger foundations, all fall under the definition. Additional adaptive channels are not consciously undertaken to protect against storms but are still included in our definition. For example, if societies transition toward service-based economies through development, thereby decreasing the supply-chain and inventory sensitivities to hurricanes, we consider this adaptive. Activities that would not fall within our definition of adaptation include insurance, as this tool financially protects the homeowner but does not decrease damages.

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 first 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 detailed variation across space is driven mainly by population rather than income per capita assumptions.

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[3]. 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 assumed by Hanson et al. (2011). Thus, the empirical evidence supports the assumption that the capital stock scales proportionately with income and population[4]. 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. Because we do not know the precise size of each storm, we proxy for 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

[3] R^2 value of 0.96.

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

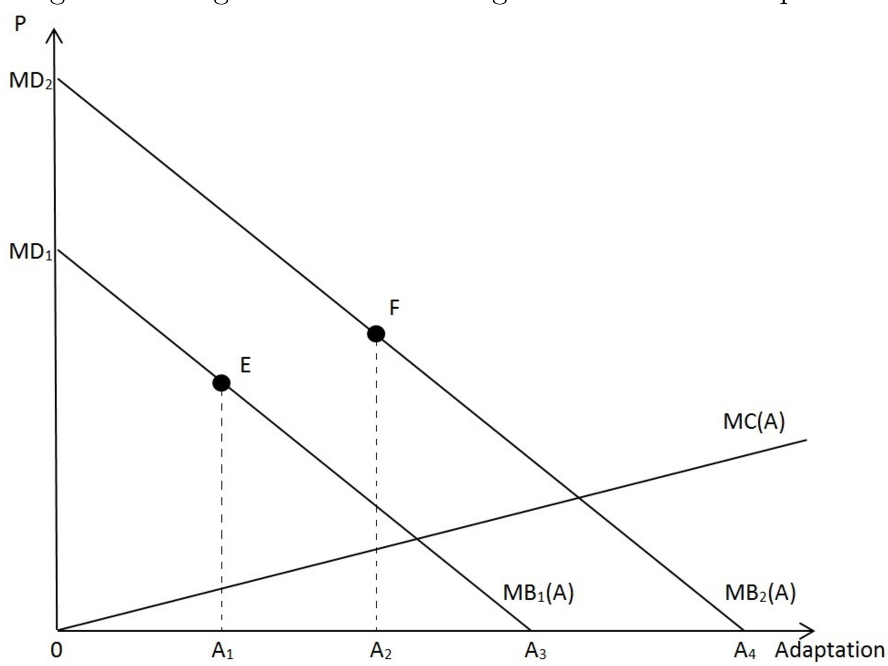
following functional form with respect to storm intensity, I, and population density, Pop:

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

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 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, 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: $D_x = \theta(A) \cdot PD_x$.

Figure 1: Marginal Costs and Marginal Benefits of Adaptation



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

[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 $\theta(A)$.

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:

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

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, $F_x = \theta(A) \cdot PF_x$:

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

[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.

We test this proposition using both cross sectional evidence across locations as well as intertemporal variation in our panel. The study 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. Note however, that 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. Thus, relative comparisons within sample can be made but there is not theoretical threshold based on our model.

Insurance is an important mechanism to cope with risks (Arrow, 1973; Kunreuther, 1996). In some cases, insurance can be a substitute for adaptation, especially when it is set at below actuarially-fair rates or coupled with subsidized post-disaster aid (Kelly and Kleffner, 2003). Because the United States has subsidized flood insurance (Michel-Kerjan, 2010), generous post disaster 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. There of course may be additional reasons why the United States is different than the rest of the world. The US may have a stronger desire to live along the coast and it may be wealthier. However, the study controls for population density as well as income per capita at the county level.

By comparing the storm damage function of the United States versus the rest of the world, one can test the assumption of the model parameters above. We postulate that the damage function for the United States reflects potential damage (zero abatement). The rest of the world exemplifies adaptation since it does not offer such generous compensation programs. In contrast, both the United States and the rest of the world should have similar fatality functions. 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. The United States damage function also offers a good test of the appropriate elasticities of the potential damage function. The United States comparison also provides a test of the constant term and the coefficient on storm intensity.

For all 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. We do not know to what extent adaptation to economic damage is a complement or substitute to adaptation to fatalities. Lastly, we do not address the costs of adaptation and therefore do not calculate the net benefits of adaptation. However, it is worth noting that the coastal protection literature concerned with sea level rise finds that it is generally cheaper to protect developed land than let it be inundated (Yohe et al., 1995; Ng and Mendelsohn, 2005; Hunt et al., 2011; Neumann et al., 2011).

2 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 with 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. This also reduces the potential for any strategic measurement error in the damage reports. Next, using our spatially refined data, we test for the importance of local versus national adaptation. Finally, we compare the elasticities of the United States to those of 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 relies primarily on the variation across space to identify parameters of interest, whereas the identifying variation for our error components model relies on 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

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

[8]See the Appendix for a detailed explanation of specification tests and explanatory variable choice.

variable 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 Appendix, 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 direct economic 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. Since the variable L_{ij} is not present in our theoretical model, as a robustness check we also drop this variable in the Appendix and find no change in the overall results. 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]. While we include near misses in our main result. In the Appendix we present results with near misses dropped, thereby allowing our empirical model to exactly replicate our theoretical model. The results do not change with the inclusion of near misses.

Unlike previous literature that aggregates up to the country-year level (Hsiang and Narita, 2012; Neumayer, 2012; Noy, 2009; Kahn, 2005), one major difference in our analysis is that our unit of observation is a country-landfall (a storm striking a country). This means that a country suffering from three storms in a year will be treated as three observations. There are several advantages. First, this ensures that any missing storms or missing data on storm impacts are not treated as zero, which could bias estimated coefficients. Second, we directly model damages and fatalities at the storm

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

level. Thus, we can use more spatially refined data, including individual storm characteristics at their point of landfall as well as sub-national socioeconomic controls. Lastly, we do not normalize cyclone impacts by population or GDP, which would imply no adaptation. Using country level GDP or population to normalize for what is in harm's way is problematic as each storm hits a different place within a country with different characteristics.

In the 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 find that OLS is appropriate when modeling the (log of) damages, as this variables follows a normal distribution rather than a Poisson or Negative Binomial distribution. 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 and what is actually being subsumed by different implementations (Greene, 2007). The results support the findings of our cross-sectional and fixed effects results. We also use the Seemingly Unrelated Regression Model to potentially leverage efficiency gains over OLS through exploitation of any correlation in the error terms. However, we do not find this changes the main results and present the results in the Appendix.

In addition to these main results, we do some robustness checks to test selected sub-samples across: levels of development, spatial scales (national versus local), and between the US and the rest of the world.

2.1 Data

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 $0.75 trillion in damages[10] and approximately 400,000 lives lost. We begin our analysis in 1960, coinciding with the start of satellites used for storm observations. Before this period, storms were incidentally observed by ships and coastal communities, or found by aircraft flying long-range patterns in search of disturbances (HRD, 2014). Thus, we have less confidence in the accuracy of storm data and human impacts before this period. Hsiang and Narita (2014) correctly note that 6,700 storms have been recorded by humans since 1950, but many of these storms do not make landfall and fewer still can be linked with direct economic damages or human fatalities. Thus, our dataset represents the full record of storms during our time period that can be matched with publicly available damages and fatalities. We present summary statistics in the Appendix.

Historical cyclone landfall damage and fatalities are from the EM-DAT Emergency Disaster Database (CRED, 2012) and Nordhaus (2010) and 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

[10]All dollar values in this paper are in terms of real 2010 $USD.

for cyclone intensity. Additionally, we include the Power Dissipation Index and Accumulated Cyclone Energy Index as cyclone intensity proxies in the Appendix.

Ideally, analyses of damages and fatalities would control for the exact population and capital impacted by the storm. However, the spatial extent of a storm is not recorded by IBTrACS for most storms[11]. Thus, many studies use country-level socioeconomic variables as proxies. We collect both country and sub-country data. We collect country-level population density and per capita 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. In addition to national data collected annually for the globe, we also collect sub-national, county-level population density and income per capita data for six large countries (Australia, China, India, Japan, Philippines, United States, and Mexico at the state-level) using official census records. Storms to these six countries represent approximately 60 percent of our sample. The remaining countries are small- to medium-sized whose national statistical more closely represent the local levels. This allows us to more accurately assess the socioeconomic conditions at landfall. Note, too, that by using income per capita (instead of national GDP) and population density (instead of total population) we can change spatial scale without impacting the overall level of damages. For

[11]The radius of maximum winds is recorded for a limited number of storms in the Northern Atlantic.

example, smaller countries should have the same damage function as larger countries. We test the importance of using country versus sub-country data in the Results section. We also test both market exchange rate and purchasing power parity definitions for income per capita and present our results in the Appendix.

Since the size of the storm, its spatial extent, varies by storms but is not accurately recorded, one cannot control for size in this study. We consequently do not know the aggregate population or capital in harm's way of each storm. We approximate what is in harm's way by using population density and per capita income in the nearest counties to landfall. This allows a much closer fit between where storms land and what is impacted than using national GDP or population. Also, since our variables are per capita or per square mile, we are also able to carefully test the benefits of using national versus sub-national data in estimating damages.

Finally, a hurricane generator is used to predict the long-term frequency for low and high intensity storm landfalls for each location. We turn to simulation data because the historical record of storm tracks is heterogeneous in quality across time and space, especially before the development of the Dvorjac technique that greatly improved accuracy in estimating hurricane strength and the large-scale satellite deployment in the 1970s (Velden et al., 2006). A total of 68,000 simulated cyclone tracks generated by Kerry Emanuel are used to predict the frequencies by location (Emanuel et al. 2006; Mendelsohn et al., 2012). 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 Appendix. 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 analysis.

With any data, measurement error is possible. In this analysis, there may be measurement error with our estimates of damage (EM-DAT), income, and cyclone intensity. All are addressed herein. The damage and fatality data are likely the largest source of potential classical measurement error and even strategic reporting bias. The bias introduced by strategic reporting could impact accuracy in both directions: countries may try to under-report damage to appear more capable, while other countries may try to over-report damage to encourage international aid, relief, and sympathy. This could be particularly true for lower income countries. Classical measurement error will cause no bias in the regression coefficients but underreporting could bias impacts downward. EM-DAT, the data provider, takes care to collect data from multiple sources and verify the accuracy of the reports. If countries consistently misreport data, then it would be observed during cross-verification by EM-DAT from reports by the UN, World Bank, Red Cross, and other organizations. EM-DAT prioritizes data from the most trusted sources. In addition, we control for potential strategic reporting through selective subsample regressions based on income, assuming that within income groups, countries will not systematically differ in their incentives to miss-report. We present our findings in the Results section and also the Appendix. We do not find evidence that strategic reporting changes our results.

Income and GDP records may also have measurement error in reporting and estimation. We test a variety of data sources, including the Penn World Table and USDA ERS International Macroeconomic Data, and both market exchange rate and purchasing power parity definitions of GDP. We also use our low versus high income partitioned regression results to address potential measurement error concerns. Assuming the measurement error is not consistent across data sources or within levels of development, similar empirical results give us confidence that potential measurement error is not a large factor biasing estimates.

Finally, measurement error is possible in the storm intensity record. Scientific ability to accurately describe storm intensity has greatly improved in the 1970s and 1980s with large scale satellite deployment and technique improvements (Velden et al., 2006). However, it is likely that minimum sea level pressure is measured with greater accuracy than maximum wind speed (Gray et al., 1991; and see our discussion in the Appendix and the Results section). We minimize any potential measurement error by using multiple proxies for storm intensity including maximum wind speed, barometric pressure, PDI, and ACE. We find that minimum sea level pressure explains both damage and fatalities more accurately than the alternative intensity measures.

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[12]. However, the definition of a tropical cyclone itself censors storms below a critical intensity. It is possible this censorship of small, low damage storms affects the estimated 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.

3 Results

This section presents our main results using cross-sectional and fixed effects specifications. We find our results robust to alternative specifications, functional forms, and additional sensitivity analyses. Our robustness checks are presented in the Results section and detailed in the Appendix. Additionally, in the Appendix, we drop near misses, presenting only the results for which the distance from landfall equals zero. This empirical specification is

[12]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).

identical to our theoretical model.

3.1 Fatalities

Table 1 shows the regression results for our fatality function using all countries. Columns 1, 2, and 3 are cross-sectional regressions. Column 1 presents a basic regression. Column 2 decomposes the underlying 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 the 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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Regression	Base	Π Split	Wind	Year FE	Year FE, Wind	Country FE	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, $\beta_1 < 0$, for all specifications, lying 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, $\beta_2 < 1$. Using the F-test, we find that the estimated elasticities are all less than one at the 99% confidence level. The population density coefficient implies that places with more people suffer more fatalities. However, the coefficient also implies that the fatalities per person are lower in more dense places. That is, from a personal point of view, cities are safer than more rural areas. 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 in cities (Lindell et al., 2011; Whitehead, 2003).

We find a divided result for the underlying storm frequency. The coefficient on the frequency of high intensity storms elasticity is negative, $\beta_5 < 0$, implying places that are often hit by powerful storms have taken precautions. 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 maladaptive 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 hazard 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.

3.2 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[13] 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 coefficient on population density varies between -0.3 and 0.07. 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

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

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 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[14]. We also use the PDI and ACE as additional proxies for storm intensity and present the results in the Appendix. One explanation of the superiority of minimum pressure as a measure of intensity is 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, reflecting 1-, 3-, or 10 minute sustained maximum wind speeds. As there is no deterministic relationship between these different measures, 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

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

of wind data (NRL, 1998). Thus, we recommend the use of minimum sea level pressure readings to be utilized for tropical cyclone damage and fatality research.

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.

3.3 Adaptation Across Income Levels

One hypothesis that has been raised with respect to adaptation is that adaptive 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 theory that people adapt 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, even overcoming the scale effect of more in harm's way. 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.

3.4 Adaptation Across Space

Using the collected national and sub-national data, we then test adaptation across levels of spatial scale. This allows us to estimate the gains from using more nuanced spatial data. Sub-national data gives us insight into local adaptation and the differences between adaptation in urban versus rural areas. National socioeconomic data allows us to identify the broad differences across levels of economic development and federal policies. Across space and time, the county-level income per capita records are highly correlated with the national levels ($\rho = 0.94$), while the population density is less correlated across spatial scales ($\rho = 0.75$). Thus, within countries, the urban versus rural population variation dominates the economic inequality across space.

In Table 5, we formally test the difference between national and sub-national adaptation. Using the 60 percent of our data that has both national and sub-national socioeconomic data, we estimate our impact functions using exclusively national-level data and then the same observations using sub-national measures. The other 40 percent of the data includes many small countries with less variation between local and national socioeconomic variables. Columns 1-4 show our fatality functions, while Columns 5-8 report our estimated damage functions. Odd columns present county-level results and even columns represent the equivalent regressions using national-level socioeconomic data. Lastly, we drop the United States in Columns 3, 4, 7, and 8. We highlight again that our population and income variables are normalized by area and population, thus allowing us to navigate up and down spatial scales without impacting the aggregate level of damages calculated. For example, one landfall may be defined by a national per capita average income of $15,000 and a local per capita average income of $20,000, but would result in similar levels of estimated damages. These tests also allay fears of our use of sub-national data in our main empirical results.

We find overall that both county- and national-level data have high explanatory power for both damages and fatalities. Although there are few statistically significant differences, the interpretation of results can yield potentially important findings. Data from the national level shows higher rates of adaptation, with slightly larger income elasticities of fatality (-0.87 versus -0.91) and damage (-0.35 vs -0.50). This highlights the importance of the overall level of development of a country allowing for better national-level adaptation, potentially including efforts in advanced storm warning systems or better coordination of post-disaster aid. Similarly, for the population density elasticity, damages show the strongest differences. Denser nations have lower (more negative) elasticities than their more rural counterparts. Similarly, within countries, rural areas have higher aggregate damages than urban areas. This striking finding highlights the importance of public adaptation in urban areas and also the potential difficulties protecting sparsely populated areas.

Table 5: Adaptation Across Spatial Scales

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable (Ln)	Fatalities	Fatalities	Fatalities	Fatalities	Damages	Damages	Damages	Damages
Ln Income Per Capita (County)	-0.737***		-0.874***		0.0589		-0.353***	
	(0.0665)		(0.0769)		(0.104)		(0.122)	
Ln Income Per Capita (National)		-0.784***		-0.905***		-0.298***		-0.504***
		(0.0636)		(0.0739)		(0.104)		(0.111)
Ln Population Density (County)	0.0672		0.0727		-0.265***		-0.260***	
	(0.0499)		(0.0547)		(0.0743)		(0.0765)	
Ln Population Density (National)		-0.0871*		-0.00154		-0.727***		-0.620***
		(0.0526)		(0.0589)		(0.0858)		(0.0834)
Ln Intensity (Pressure)	-16.03***	-15.26***	-15.75***	-15.09***	-28.26***	-33.46***	-21.70***	-24.40***
	(2.593)	(2.557)	(2.747)	(2.703)	(4.041)	(3.799)	(4.190)	(3.934)
Ln Landfall Distance	-0.171***	-0.168***	-0.157***	-0.159***	-0.499***	-0.408***	-0.498***	-0.434***
	(0.0323)	(0.0323)	(0.0337)	(0.0336)	(0.0673)	(0.0648)	(0.0634)	(0.0608)
Ln Count Low	0.246	0.556**	0.409	0.516**	2.680***	3.537***	3.054***	3.407***
	(0.311)	(0.259)	(0.324)	(0.261)	(0.534)	(0.446)	(0.524)	(0.408)
Ln Count High	-0.252**	-0.332***	-0.369***	-0.413***	-1.457***	-1.756***	-1.727***	-1.824***
	(0.119)	(0.107)	(0.124)	(0.110)	(0.209)	(0.184)	(0.206)	(0.170)
Constant	118.8***	111.6***	117.1***	112.3***	194.0***	227.2***	150.1***	168.3***
	(18.37)	(17.94)	(19.49)	(18.99)	(28.59)	(26.32)	(29.46)	(27.36)
Observations	574	574	518	518	497	497	389	389
Spatial Scale	County	National	County	National	County	National	County	National
USA Included?	Y	Y	N	N	Y	Y	N	N
R-squared	0.259	0.269	0.267	0.278	0.306	0.378	0.342	0.413

Standard errors in parentheses
** p<0.01, ** p<0.05, * p<0.1

3.5 The United States

The United States has been dropped as an outlier in earlier global studies of tropical cyclone impacts (Hsiang and Narita, 2012). Here, we utilize the economic damage results from the United States as an example of potential damage (no adaptation). We first test to see if the United States is different from the rest of the world, and then decompose the rest of the world into highly and lesser developed nations to test for additional differences.

We first test to see if the estimated damage and fatality coefficients for the United States are different than the rest of the world using both an F-test and Chow Breakpoint test. We first conduct an F-test by including an indicator variable for the United States (1 if USA, 0 otherwise). We then interact this variable with the included variables, to allow for slope variation. We then test if the sum of all US estimated coefficients is statistically different from non-US coefficients. For damages, we calculate an F-statistic of 30.90, rejecting the null hypothesis that the US and rest of the world coefficients are equal to each other at more than the 0.1 percent level. For fatalities, we calculate an F-statistic of 2.26 and fail to reject the null hypothesis that the US and the rest of the world are the same at the 10 percent level.

We also conduct the Chow Breakpoint test to determine if the estimated coefficients of subsamples of the entire sample are statistically different from each other. It does not, however, test if the sample is optimally partitioned. We perform the Chow breakpoint test on the USA and non-USA subsample regressions. For the damage regressions, we calculate a chi-squared statistic of 60.32, rejecting the null hypothesis at the 0.1 percent level that the coefficients of the explanatory variables are the same across sub-groups of the data. For the fatalities regressions, we calculate a chi-squared statistic of 3.54 and fail to reject the null hypothesis at even the 40 percent level. Thus, we conclude that the United States has a similar fatality function as the rest of the world but a very different damage function.

Table 6 compares the regression results estimated by subsamples from the United States, OECD countries excluding the United States, and non-OECD countries. Results for both minimum pressure and wind speed are presented. We find that the income elasticity of the United States varies between 1.1 and 1.6 which is consistent with 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 which is consistent with adaptation. The population density coefficient is negative for the United States which is not consistent with the zero adaptation case. We consequently conclude that the coefficient on population density is not a good test of adaptation. A storm that strikes American cities causes less damage than a storm that strikes rural areas. The discrepancy is more marked than in any other country. The effect of storm 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.

How much higher would damages be across the globe if the rest of the world did not adapt, and how much lower would damages be in the US if it adapted like the rest of the world? We use our estimated impact function to calculate these counter-factual scenarios. We use the US coefficients as the example of zero adaptation and the rest of the world as the example of 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 \$0.8 billion instead of the current \$15.3 billion. If the rest of the world had the same damage coefficients as the US, non-US global damages would be \$208 billion per year instead of the current \$10.4 billion. There is a 20 fold difference between the estimated damage function for the US and the rest of the world. Thus, we find that adaptation matters greatly in driving a large wedge between potential and observed impacts.

Table 6: 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: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

3.6 Robustness

We present our robustness results in the Appendix. We first provide evidence of our capital formation assumption, showing that capital scales linearly with changes in income and population. We also present our sensitivity analysis. Our main empirical results are robust to alternative variables, functional forms, and additional sensitivity analyses. We carefully test the shape of the damage and fatality functions, including linear, log-linear, quadratic, and cubic specifications. We test the impact of data definitions and additional proxy variables through the use of both market exchange rate and purchasing power parity income and GDP per capita. We also test different proxies for storm intensity including maximum wind speed and minimum sea level pressure, as well as both the Power Dissipation and Accumulated Cyclone Energy indices. An additional robustness check drops "near misses", or hurricanes that do not directly make landfall in a country, presenting only the results for which the distance from landfall equals zero. This empirical specification is identical to our theoretical model. We find that across all of these specifications, our main results hold.

We also test different estimators, including the negative binomial estimator and the Seemingly Unrelated Regressions (SUR) model. Since we use identical regressors in both our equations, there is no efficiency gain in the SUR model relative to the OLS model (Greene, 2003). We test the applicability of a cross-equation coefficient restriction, but find the estimated coefficients in the damages and fatalities equations to be statistically different from each other, thereby negating the motivation of imposing equality. This makes theoretical sense; storm and human factors may impact damage and fatalities in different and independent ways. We also provide additional income bins and estimate income elasticities of damage and fatalities across twelve levels of development. We lastly present results comparing fatalities in the United States to that of the rest of the world. Across all of our robustness checks, we find additional confirmation of the conclusions from our main empirical results.

4 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 also test if there is a negative relationship between impacts and the underlying storm frequency. We decompose these main findings into adaptation across level of development and spatial scale. We find clear evidence of adaptation in most of these tests. The coefficient of population density may not be a good test of adaptation. Nonetheless, 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. State but mostly federal policies compensate potential victims of hurricanes. 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 storm 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? 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 program 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 encourage 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, with limited incentive to retreat to safer locations and no incentive to invest in physical protection.

This research reveals adaptation to tropical cyclones is ongoing in most of the world and it dramatically reduces damage and fatalities. 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, state, and federal 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. Specifically, federal programs have eliminated the incentive for private individuals and firms as well as local and state governments to adapt to reduce damage per storm. This leads to over-capitalization in high risk areas that drive up aggregate observed damage 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 public 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[15]. It appears there are still at least two countries that can significantly 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 tropical cyclones 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.

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

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