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 fourteen times higher than other developed (OECD) countries. (JEL D81, O1, O2, Q54, Q56, R5)

Over the last decade, the average annual global damage from tropical cyclones (hurricanes) has reached $26 billion dollars with 19,000 lives lost (Mendelsohn et al., 2012; CRED, 2012).[1] These losses measure the remaining damage and fatalities given existing adaptation. But what would the damage and life lost have been if no adaptation had occurred? What evidence exists that there have been any adaptations? This paper seeks to quantify the answers to these questions from an empirical analysis of the damage and fatalities caused by individual tropical cyclones from around the world.

[1]These figures represent the average damages and fatalities from 1990 to 2008. If two very high fatality outlier landfalls are excluded, the average fatalities per year drops to approximates 4,300.

The literature on natural hazards has long been concerned about adaptation. Analysts have explored whether development or institutions lower the toll taken by earthquakes, cyclones, floods, and fires (Kahn, 2005; Toya and Skidmore, 2007; Kellenberg and Mobarak, 2007; Fankhauser and McDermott, 2014). This hazard literature has found evidence that income matters, suggesting that people and governments do significantly reduce the mortality rates from natural hazards as they get wealthier. Past studies have also examined whether countries that experience frequent hazards have lower residual impacts (Fankhauser and McDermott, 2014; Hsiang and Narita, 2012; Neumayer et al., 2014; Schumacher and Strobl, 2011; Keefer et al., 2011).

This study uses tropical cyclones to examine this question more precisely. The advantage of looking at just one type of hazard is that one can carefully account for the intensity of that hazard, which turns out to be a very important explanatory factor. For example, wind tunnel experiments reveal that damage increases with the cube of wind speed (Emanuel, 2005; Emanuel 2011). Wind experiments also imply that if you placed twice as much assets in the wind tunnel, there would be twice as much damage. Because GDP is generally proportional to assets, empirical work on tropical cyclones have "normalized" damage by dividing damage by GDP (Hsiang and Narita, 2012; Nordhaus, 2010; Pielke et al., 2008; Pielke and Landsea, 1998). The cyclone literature is effectively assuming that the elasticity of GDP/capita (income) and population are unitary. Similarly, dividing fatalities by population normalizes fatality risk (Kahn 2005) but also implicitly assumes that the population elasticity of fatalities is unitary.

In this paper, we argue that these normalization assumptions of the literature are reasonable predictors of potential impacts, what one would expect if there is no adaptation. Without adaptation, the damage function should have an income elasticity of 1, the fatalities function should have an income elasticity of zero, and population or population density should have an elasticity of 1 in both the income and fatalities function. We empirically measure the actual elasticities of both income and population for both the fatality and damage function. We use as a measure of adaptation the extent to which predicted damage from these empirical functions is less than potential damage.

We follow Hsiang and Narita (2012) by examining global tropical cyclones. However, our empirical analysis is different in several key ways. First, we test hypotheses about the elasticity of income and population to measure adaptation. Second, we use each storm as a separate observation. Hsiang and Narita average the storms striking a country each year. Unfortunately, storm damage is a highly nonlinear function of storm intensity. Averaging the characteristics of storms seriously biases the results. Third, we supplement the available data on damage and fatalities by collecting information about the intensity of each storm and the precise location it struck land. We then measure the income and population density near that contact point. For small countries, we use each country as the observation as did Hsiang and Narita. For larger countries, however, we rely on subnational observations.

Using subnational observations in large countries is important because the affected areas may have higher incomes and population densities (as in the US) or lower incomes and population densities (as in Australia) than the national average. We then regress the observed damage and fatalities per storm on the cyclone intensity as well as the population density and income of the affected area. Finally, we follow Hsiang and Narita and test the whether storm frequency affects observed damage and fatalities. However, instead of using the frequency of all cyclones, we include the predicted frequency of both low and high intensity storms.

The paper finds ample evidence of adaptation around the world. The results suggest that countries and private actors have taken effective measures to reduce the potential damage and the potential fatalities from tropical cyclones. An important exception to this rule is the income elasticity of damage in the United States which is unitary implying no sign that adaptation is being undertaken (although fatalities have been reduced). Although the United States is struck by only 4% of global cyclones, cyclone damage in the United States is 60% of the global damage. Cyclone damage in the United States may also be an example of potential impacts (no adaptation).

1 Theory

Faced with a set of risks, firms, individuals, and governments often take steps to protect themselves and reduce potential risk. We define risk reduction (tropical cyclone adaptation) as any action that reduces the expected damage or fatalities from a storm. These include actions taken far in advance of any storm and actions taken as a storm approaches. They consider both actions taken by governments and actions taken by private citizens and firms. For example, improvements in forecasting and tracking as well as advanced warning systems are known to be effective tools to reduce fatalities because they allow people to take precautionary measures. Large infrastructural development in flood protection including levees, river channelization, mangrove plantations, and beach nourishment can protect people and property from storm surge and fresh water flooding. Improvements in building codes can lead to stronger and more resilient dwellings that resist high winds and floods. Zoning ordinances can keep people and buildings away from high risk locations. Increased urbanization may also be an adaptation if it automatically pushes people towards sturdier multiple unit dwellings and more effective local governments. Insurance and relief programs do not eliminate risk, they merely compensate affected parties. Fair insurance can facilitate adaptation because the premiums provide a clear measure of the expected risk. Similarly, subsidized insurance may reduce adaptation by effectively understating the risk to policy holders. In the extreme, free insurance would encourage actors to make no adaptations since they are fully compensated no matter what happens.

Adaptation drives a wedge between observed and potential damage and fatalities (Brooks, 2003; Fankhauser and McDermott, 2014). 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 rely on empirical evidence to link capital stocks with income and population.[2] 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 Hansen et al. (2011). We 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. Potential damage is assumed to be proportional to the per capita capital stock, K, as composed of the population struck by

[2]Graphs and additional supporting evidence are available in the Appendix.
[3]R^2 value of 0.96.

the storm, Pop, and the affiliated per capita income, I. Since we do not have a measure of the actual size of each storm, we assume that the population affected by a storm can be measured using the average population density at the location where the storm first strikes land. A majority of the damage from most tropical cyclones occurs in the coastal counties near where the storm lands (Strobl, 2011). Potential damage is also a function of the intensity of the storm, I, which we measure using maximum wind speed and minimum pressure. We assume (but later test) that intensity has a constant elasticity with respect to damage. Potential damage has the following functional form:

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

Similarly, we assume that the potential fatalities per storm, PF_x, is proportional to population density, Pop, and has a constant elasticity with respect to storm intensity, I,:

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

With no adaptation, income does not enter the potential fatalities function. People of every income are equally likely to die from the event 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 ($\frac{dPD}{dI} > 0$

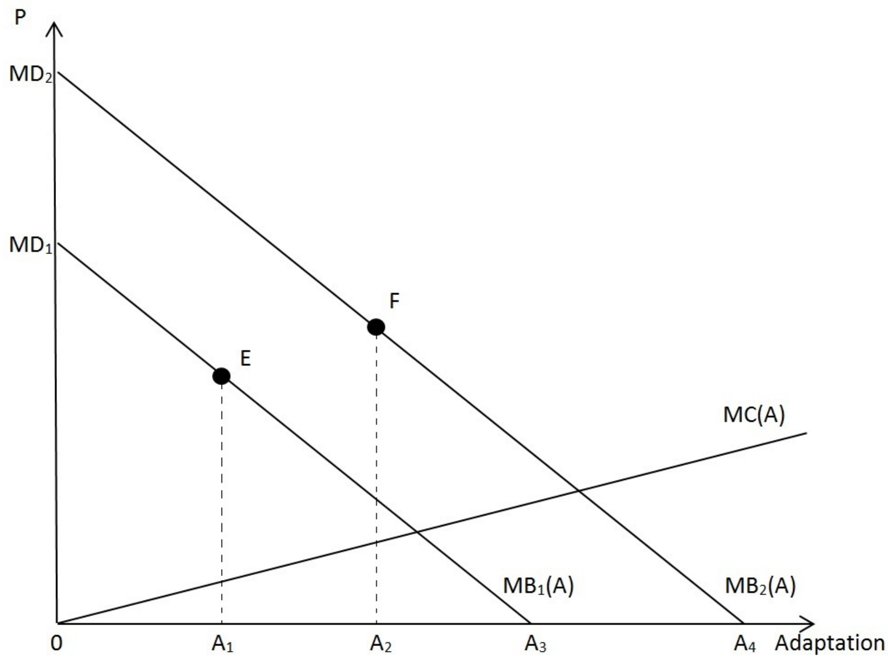
and $\frac{dPF}{dI} > 0$).

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 function 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 potential damage removed, $\theta(A)$, 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.[4] 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]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 ($\frac{dA}{dY} > 0$), ($\frac{dA}{dPop} > 0$)[5], ($\frac{dA}{d\Pi_l} > 0$) 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

[5]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.

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

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

The test can be a comparative static analysis if it relies on cross sectional evidence from one country to another. The test can be dynamic if it relies on inter-temporal changes within a country. In both cases, the analysis 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 coefficients of the constant term and of the intensity of storms is not known and so cannot be used to test for adaptation. Relative comparisons within the sample can be made but there is no theoretical threshold for the constant and intensity coefficients.

We assume that coefficients below these critical values are evidence of adaptation and not something else. Of course, there may be omitted variables that explain why coefficients are greater than zero that are circumstantial rather than a reflection of adaptation. For example, urban dwellers may be more educated and so take more precautions than less educated rural people. This may lead the population density variable to have a negative coefficient but it is really education that is driving the adaptation, not population.

In this study, 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 combined effect of private individuals, firms, and governments. We do not know to what extent adaptation to economic damage is a complement or substitute to adaptation to fatalities. We also do not know how the direct hurricane losses relate to longer-term recovery or other important fiscal costs of hurricanes (Deryugina, 2013). Lastly, we do not address the costs of adaptation and therefore do not calculate the net benefits of adaptation. However, much literature finds that benefits can often far outweigh costs for coastal adaptation to salt water inundation from sea level rise (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 through cross-sectional and panel techniques[6]. The resulting estimated coefficients can be interpreted as elasticities. We then test to see if these elasticities are different from the values expected with no adaptation. We refine these tests by estimating several regressions across different subsamples. For example, we partition countries into low income and high income nations and examine the coefficients for each subsample. We also compare dense and lightly populated countries. Using just the sample of subnational observations, we also compare the impacts of storms that struck rural versus urban commu-

[6]Count data estimation are shown in the Appendix. The results support the findings of our cross-sectional and error components models. We also test a Seemingly Unrelated Regression (SUR) approach, but due to the fact that our explanatory variables across the damages and fatalities equations are identical in this analysis, there is no efficiency gain relative to OLS and the estimated coefficients are identical.

nities. Finally, we compare the elasticities of the United States, the rest of the OECD, and the rest of the world.[7]

We use both a cross-sectional model and an error components model with country and time fixed effects to calculate damage and fatality functions. Cross-sectional analysis uses variation across time and space to identify parameters of interest, whereas the 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, the within-country and within-year variation will not capture adaptive changes on these broader scales. However, cross-sectional analysis may be confounded by time-invariant omitted 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.

Guided by rich previous scientific justification for a power model relationship between damage and wind speed (Emanuel, 2005; Emanuel 2011; Pielke and Landsea, 1999), and acknowledging that wind, alone, does not completely determine impacts (Powell and Reinhold, 2007), we test various

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

functional forms and model specifications (see Appendix). Ultimately, we affirm the previous literature and also find that the log-log functional form is the best fit. Therefore, we model damages for cyclone landfall j at time t in country i as:

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

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_{ijt} is direct economic damages and F_{ijt} 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[8]. While we include near misses in our main result, we present results with near misses dropped in the Appendix, thereby allowing our empirical model to exactly replicate our theoretical model. The results do not change with the inclusion of near misses.

Unlike the previous literature that aggregates events to country-year averages (Hsiang and Narita, 2012; Neumayer et al., 2014; Noy, 2009; Kahn, 2005), one major difference in our analysis is that our unit of observation is a single storm striking a country. This means that if three storms strike a single country in one year, we treats this as three observations. There are several advantages to this approach. First, this ensures that any missing storms or missing data on storm impacts are not treated as zero and therefore change the measurement of damage in an observation. Second, we directly model damage and fatalities at the storm level. Thus, we can use more spatially refined data, including individual storm characteristics at their point of landfall instead of national averages. We can also include the income and population density of the region actually affected by the storm

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

instead of using national average statistics. Lastly, we do not normalize the dependent variable, cyclone impacts, by population or GDP, but rather both as independent variables in the regression.

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 damage, as this variable 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 the proper implementation of fixed effects in these models (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 estimate elasticities to test selected sub-samples including elasticities across: levels of development, spatial scales (national versus local, presented in the Appendix), urban versus rural, and amongst the United States, other OECD countries, and the rest of the world. The income elasticity in the United States damage function implies that there is no adaptation to damage in the United States. One final comparison utilizes the results of this last set of regressions to compare what would happen in each region if it had the climate coefficients of another region. For example, we compare the cyclone damage that would happen in the United States if the United States had the coefficients of the rest of the OECD.

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. The cumulative damage from these storms totals almost $0.75 trillion [9] and approximately 400,000 lives lost. We drop observations from before 1960 because global observations of earlier storms were more erratic and estimates of damage and lives lost were unreliable (HRD, 2014). Hsiang and Jina (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 damage or human fatalities. Thus, our dataset represents the full record of storms between 1960 and 2010 that can be matched with publicly available damages and fatalities. We present summary statistics in the Appendix.

Historical cyclone landfall damages and fatalities records from the 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

[9] 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[10]. Most cyclone 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 v7.1[11], 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, secondary political unit (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. This represents approximately 60 percent of our sample of storms. The remaining countries are small- to medium-sized whose national statistics 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

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

[11] Based on Johnson, Larson, Papageorgiou, and Subramanian (2009) comparison on the new Penn World Table results, we also test the Penn World Table v8 results. We find no change in our results. See also our discussion in the Appendix.

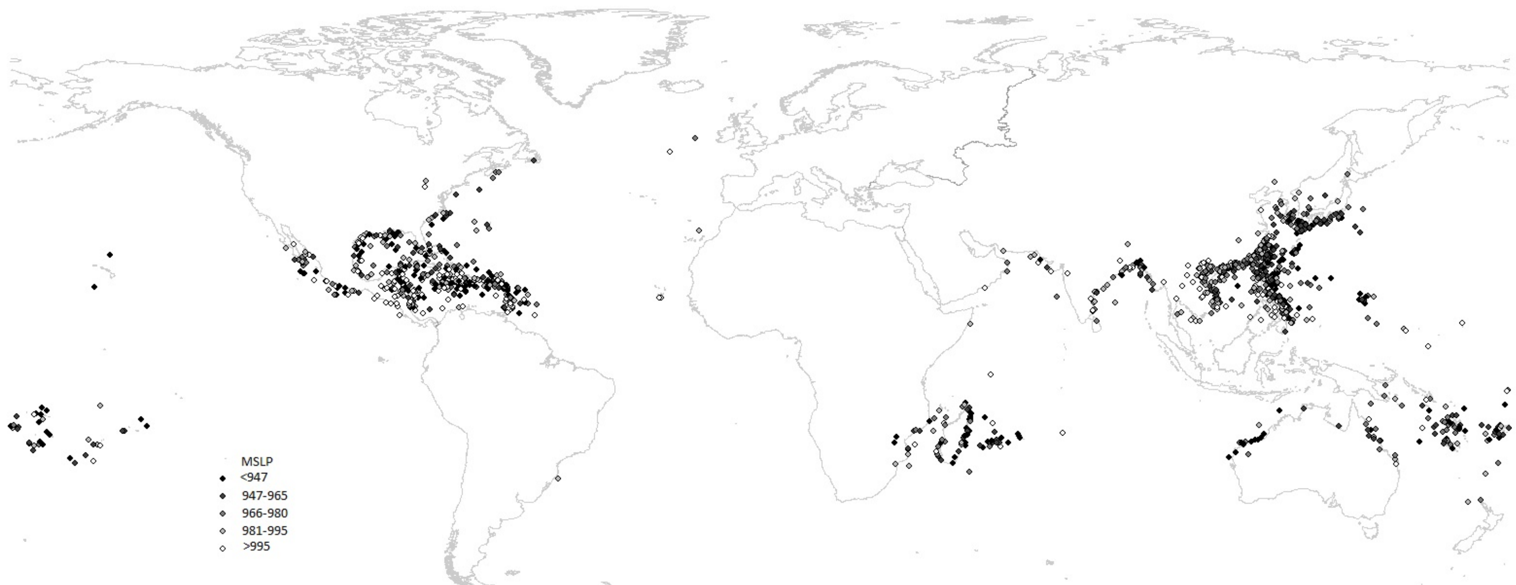
can change spatial scale without impacting the overall level of damages. For example, if our relevant geographic unit is half as large as the country, our estimated damages and fatalities will not be half the magnitude. We test the importance of using country versus sub-country data in the Appendix. We also test both market exchange rate and purchasing power parity definitions for income per capita and present our results in the Appendix.

Except for small islands, most storms only affect a fraction of the people and capital of a nation. By relying on subnational measures for large countries, we seek to reduce the measurement error associated with using national statistics. This may well result in much larger coefficients compared to national scale studies. Further, by carefully measuring the effect of per capita income rather than simply dividing damage by GDP, we expect to more faithfully measure the underlying damage function. Similarly, by including population density rather than simply dividing fatalities by national population, we expect to get a much more accurate measure of the tropical cyclone fatality function.

Finally, a hurricane generator is used to predict the long-term frequency for low and high intensity storm landfalls for each location (Emanuel et al,, 2008). We turn to simulation data because the historical record of storm tracks is thin and heterogeneous in quality across time and space. This is especially true before the development of the Dvorjac technique that greatly improved accuracy in estimating hurricane strength and the large-scale satellite deployment in the 1970s that improved measurement (Velden et al., 2006).

A total of 68,000 simulated cyclone tracks generated by Kerry Emanuel are used to predict the frequencies by location around the world (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 the Appendix. We map the storm observations by storm intensity (minimum sea level pressure) in Figure 2. Altogether, 87 countries report damage from tropical cyclones and they are all represented. Only observed landfalls are included in the database except for islands. Because some small islands were observed to have hurricane damage even though they were not struck by the eye of a hurricane, we also include a small set of near misses for islands. With the near misses, we record how close the eye came to the island.

Figure 2: Observations by Storm Intensity



With any data, measurement error is possible. In this analysis, measurement error is a potential concern for impacts (EM-DAT), socioeconomic variables, and cyclone intensity (IBTrACS) data. All are addressed herein. The damage and fatality data are a potential 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. Poor countries may simply not have the resources to measure damage accurately. Classical measurement error will cause no bias in the regression coefficients but systematic errors may cause bias. EM-DAT, the data provider, takes care to collect data from multiple sources and verify the accuracy of the reports. If countries consistently misreported 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 sub-sample regressions, assuming that within groups, countries will not systematically differ in their incentives to mis-report. We present our findings in the Results section and also the Appendix. If strategic reporting does exist, we do not find that it fundamentally changes our results.

Income and GDP records may also have measurement error in reporting and estimation. As such, we use a variety of data sources, including the Penn World Table and USDA ERS International Macroeconomic Data, and test both market exchange rate and purchasing power parity variable definitions. 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.

There is some measurement error in the storm intensity record. Scientific ability to accurately describe storm intensity greatly improved in the 1970s and 1980s with large scale satellite deployment and technique improvements (Velden et al., 2006). We consequently compare the results using multiple proxies for storm intensity including wind, pressure, PDI, and ACE. The results are comparable. However, we find that minimum sea level pressure is the best explanatory variable of intensity, leading to the best fit (Gray et al., 1991; and see our discussion in the Appendix and the Results section). We consequently emphasize the minimum sea level pressure results in the text. Alternative results are shown primarily in the Appendix.

EM-DAT is the best publicly available source of global natural disaster data (Tschoegl et al., 2006; Guha-Sapir and Below, 2002) but they do not record all historical cyclone landfalls. EM-DAT censors low impact storms with minimum damage and fatality criterion[12]. Low impact storms that hap-

[12]A cyclone must meet at least one of the following criterion to be included in EM-

pen to cause few deaths or little damage are not recorded. This was especially problematic in the early years of EMDAT and explains why we did not use data before 1960. This censuring of less harmful storms could potentially cause the coefficient on intensity to be underestimated. To test for the importance of this effect, we compare an OLS estimator with a time fixed effect estimator of the damage and fatality functions. Controlling for time should reduce the bias from the censuring by controlling for the difference between missing data in the early years versus the late years of the data set. If the coefficient on intensity goes up with the time fixed effect model, it is suggestive of an important bias from censoring. In addition, storms in the early part of our data may be missing due to a lack of observation or reporting. In the Appendix, we present results of our damage and fatalities functions using only observations from countries that reported storms throughout the sample. In addition, drop all observations before the advent of major global satellite programs beginning in 1970. We find no relevant changes in our results.

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

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).

presented in the Results section and detailed in the Appendix. Additionally, in the Appendix, we drop near misses, presenting only storms where the eye of the storm struck landfall.

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	Split Frequency	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 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. Even though the elasticity is positive (fatalities increase when urban area are hit), the fatalities per person falls. Urban areas are still safer than rural areas for an individual. This result may be due to urban policies such as evacuation plans and building standards, stronger local governments with more health and rescue resources, or simply an incidental 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 is negative, $\beta_5 < 0$, implying people are adapting to more frequent intense storms by taking more precautions. These results are similar to the finding of Hsiang and Narita (2012) for tropical cyclone frequency. Keefer et al. (2011) also find similar results with lower fatalities from earthquakes in areas hit more frequently. However, we find the opposite result for the frequency of low intensity storms, (Π_L), as these 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 against the practice in the literature of assuming that low intensity and high intensity events would have similar responses (Fankhauser and McDermott, 2014; Hsiang and Narita, 2012; Neumayer et al., 2014; Schumacher and Strobl, 2011; Keefer et al., 2011).

Table 2: Evidence of Adaptation to Damages

Dependent Variable: Log Damages

Regression	(1) Base	(2) Split Frequency	(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 0.03 to 0.45. 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) a unitary income elasticity.[14]

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

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

[14]These results are also consistent with the findings of Hsiang and Narita (2012). They scale damages by GDP, so the resulting test for adaptation would be an elasticity of less than zero, as opposed to our elasticity test of less than 1 without the damage normalization. Hsiang and Narita (2012) find statistically significant semi-elasticities of between -0.2 and -0.4, evidence of adaptation.

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 5 and 9 (Mendelsohn et al., 2012; Nordhaus, 2010).

Based on the Vuong (1989), AIC, and BIC tests, minimum sea level pressure provides a better fit than wind speed[15]. Minimum pressure may also reflect other features of the storm such as storm surge and size. It is also likely that wind speed may be measured with greater error than minimum sea level pressure (Gray et al., 1991). Wind speed calculations 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 different places using winds measured for 1-, 3-, or 10 minute sustained periods. As there is no deterministic relationship between these different measures of sustained wind speeds, statistical averages must be used to convert them, leading to measurement error. 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). We also use the PDI and ACE as additional proxies for storm intensity and present the results in the Appendix. None of these

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

measures are as effective as minimum pressure and so we recommend the use of minimum sea level pressure readings to be utilized for damage and fatality research.

Table 3: Adaptation to Fatalities: Low and High Income Locations

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 Locations

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 different for low versus high income locations.[16] We create sub-samples of the data for low income (<\$6,500) and high income (>\$20,000) locations. We use locations and not countries to make this delineation. High income locations come mainly from developed countries but also from wealthy urban centers in emerging countries. The low income areas come from the least developed countries and poor rural areas in emerging countries. The differences are not strictly driven by national policies but also reflect within country differences between wealthy versus poor areas. Additional income bins are presented in the Appendix. 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

[16]Income, here, is defined as the actual per capita income of the location in the year of observed landfall. Therefore, locations can move into and out of of the income definitions through development. We also present permanent, country-specific definitions based on their status in the Organization of Economic Cooperation and Development (OECD) in alternative specifications presented in section 3.5 as well as section F in the Appendix.

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.

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. The adaptation increases rapidly with income. The high income location elasticities are statistically different from the elasticities of low income locations at the 99% confidence level. The results for higher income locations imply an income elasticity of about 2 for the value of life. This is much higher than the results in the value of life literature (Viscusi and Aldy, 2003; Viscusi, 1993) which are closer to the results for places with low incomes. 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. Lastly, we note that by grouping countries together by income level, we can minimize bias introduced by any potential non-reporting of storm impacts. The intensity coefficient is larger for wealthier countries, consistent with poor countries underreporting small storms, but the coefficients are not statistically different. Therefore, we believe any bias introduced by non-reported storms is likely to be small.

3.4 Adaptation Across Urban Versus Rural Areas

The large country data set also allows us to compare the national versus the local importance of population density. We make two comparisons. First, we compare countries with higher than average population density versus countries with lower than average density. Second, we compare where storms struck urban versus rural localities. Do dense (more than 200 people per kilometer squared) versus sparse nations react differently to storms? Do urban versus rural communities react differently to storms? The fatality results are shown in Table 5. Column 1 (dense) and Column 2 (sparse) compare the fatality regressions for different countries. The income coefficient is negative in both regressions but it is significantly more negative for more dense countries. The population density is negative and significant only for dense countries. The only other coefficient that is significantly different between the two sets of countries is the frequency of high intensity storms. More dense countries reduce fatalities in response to being hit more frequently by intense storms whereas less dense countries do not respond. All these results suggest that more dense countries are more actively engaged in reducing fatalities (adaptation) compared to less dense countries.

Column 3 and Column 4 of Table 5 examine the fatality regressions of urban versus rural localities. The results are quire similar to the national results. The urban coefficient on population density is negative whereas the rural coefficient is positive, though significantly less than one. More frequent low and high intensity storms decrease deaths in urban areas but not in rural areas. All of these results suggest that adaptation is more active in urban compared to rural localities. The one piece of information that suggests urban areas are more at risk concerns their response to storm intensity. The intensity coefficient is significantly more negative for urban counties implying they are more vulnerable to more intense (lower pressure) storms. More intense storms lead to more deaths in urban areas compared to rural areas. Although urban areas generally reduce fatalities more than rural areas, they have more difficulty reducing the deaths associated with more powerful storms.

We make similar comparisons about the damage function in Table 6. Damage in more dense nations is more sensitive to population density. The most dense countries in the dense sample have lower damage per storm. More dense countries also have a lower sensitivity to intensity. The damage in sparse countries is more sensitive to more powerful storms. So there is evidence that population density at the national level generally increases adaptation.

Comparing urban versus rural local effects, the local damage results are often consistent with the national damage results. For example, population density has a bigger negative effect on damage in cities than in rural areas. However, some of the results are different when comparing local areas. Local income is negative for urban areas but positive for rural areas. In fact, the income coefficient for rural areas is not significantly different from 1 implying no adaptation in rural areas. Another significant difference between urban and rural counties is their response to the frequency of high intensity storms. More frequent powerful storms reduce the damage per storm in both areas but the reduction is three times as large in urban areas.

The overall results suggest that there is more adaptation happening in cities compared to rural areas and in countries with higher population density. But there are exceptions to this rule such as the higher sensitivity of fatalities and damage to storm intensity in cities versus rural areas.

Table 5: Fatalities Functions: Urban Versus Rural

	(1)	(2)	(3)	(4)
Population Density	Dense Nation	Sparse Nation	Urban Locality	Rural Locality
Variables	Ln Fatalities	Ln Fatalities	Ln Fatalities	Ln Fatalities
Ln Income Per Capita (County)			-0.700***	-0.518***
			(0.0939)	(0.106)
Ln Income Per Capita (National)	-1.103***	-0.510***		
	(0.189)	(0.110)		
Ln Population Density (County)			-0.253**	0.190**
			(0.102)	(0.0823)
Ln Population Density (National)	-0.390***	0.119		
	(0.119)	(0.123)		
Ln Intensity (Pressure)	-13.10***	-14.29***	-20.31***	-11.76***
	(3.667)	(3.583)	(4.396)	(3.090)
Ln Landfall Distance	-0.168***	-0.283***	-0.226***	-0.161***
	(0.0369)	(0.0648)	(0.0493)	(0.0406)
Ln Count Low	1.135	0.302	-1.282***	0.391
	(0.851)	(0.344)	(0.454)	(0.500)
Ln Count High	-0.955***	0.0682	-0.504***	-0.0381
	(0.191)	(0.159)	(0.183)	(0.184)
Constant	100.3***	101.0***	171.8***	83.21***
	(27.69)	(24.52)	(30.78)	(22.09)
Observations	296	278	278	296
Spatial Scale	National	National	County	County
R-squared	0.342	0.306	0.369	0.254

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

Table 6: Damages Functions: Urban Versus Rural

	(1)	(2)	(3)	(4)
Population Density	Dense Nation	Sparse Nation	Urban Locality	Rural Locality
Variables	Ln Damages	Ln Damages	Ln Damages	Ln Damages
Ln Income Per Capita (County)			-0.385***	0.770***
			(0.146)	(0.156)
Ln Income Per Capita (National)	-0.446	0.248		
	(0.474)	(0.168)		
Ln Population Density (County)			-0.705***	0.0817
			(0.205)	(0.0978)
Ln Population Density (National)	-1.168***	-0.300*		
	(0.245)	(0.175)		
Ln Intensity (Pressure)	-26.93***	-42.75***	-33.80***	-26.76***
	(5.763)	(5.253)	(7.174)	(4.550)
Ln Landfall Distance	-0.432***	-0.479***	-0.504***	-0.491***
	(0.0672)	(0.135)	(0.125)	(0.0739)
Ln Count Low	2.829	4.337***	2.228***	1.377
	(2.094)	(0.590)	(0.790)	(0.857)
Ln Count High	-1.981***	-1.855***	-2.216***	-0.619**
	(0.447)	(0.271)	(0.363)	(0.310)
Constant	197.4***	275.4***	251.7***	184.0***
	(47.24)	(35.19)	(50.63)	(32.44)
Observations	192	305	219	278
Spatial Scale	National	National	County	County
R-squared	0.513	0.307	0.328	0.406

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

3.5 Comparing United States Versus Global Damages

Earlier tropical cyclone studies have noted that the damage in the United States appears to be an outlier compared to the rest of the world (Schumacher and Strobl, 2011; Hsiang and Narita, 2012). The results from previous damage estimates using United States data are also different from the global results (Nordhaus, 2010; Mendelsohn et al., 2012). We consequently test whether the damage function of the United States is different from the damage function for the rest of the world. We seek to understand why the United States appears to have much higher damage per storm. We calculate an F-statistic of 30.90, rejecting the null hypothesis that the United States damage coefficients are equal to the rest-of-the world coefficients at the 0.1 percent level. In contrast, for fatalities, we calculate an F-statistic of 2.26 and fail to reject the null hypothesis of similarity 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. 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 explanatory variables have the same relationship on 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. So the American damage function is significantly different than the rest of the world but the fatality function is not.

For our final analysis of adaptation, we compare the United States with just the other countries from the OECD and estimate a damage function for each region (see Table 7). This is a more careful comparison because it controls for the level of development. We find that the American constant, coefficient on storm intensity, and income elasticity is significantly larger than the results for the other-OECD countries. These three variables explain why the American damage per storm is higher. Working in the opposite direction, the American coefficient on population density is more negative which reduces the damage relative to the other OECD countries.

We then calculate what the American damage would be if we used the damage coefficients for the other-OECD regression. The damage per storm would fall from $2.0 billion to $166 million, over an order of magnitude drop. The aggregate annual damage from tropical cyclones in the United States would fall from $15.3 to $1.2 billion. We also estimate the damage in the other-OECD countries if they had the damage function of the United States. The damage per storm in the other OECD countries would increase from $231 million per storm to $9.4 billion, a forty fold increase. There is no question that the United States is far more vulnerable to tropical cyclones than other similar countries, controlling for the frequency and intensity of storms and for income and population density.

Table 7: United States vs Other OECD Damages

	(1)	(2)	(3)	(4)
Countries	USA	USA	OECD & non-USA	OECD & non-USA
Regression	Base	Wind	Base	Wind
Ln Income per Capita	1.148**	1.636***	-0.624	-0.459
	(0.548)	(0.555)	(0.395)	(0.424)
Ln Population Density	-0.300	-0.342	0.298***	0.309**
	(0.266)	(0.284)	(0.0707)	(0.131)
Ln MSLP	-84.75***		-34.35**	
	(7.969)		(14.03)	
Ln Maximum Wind		5.069***		2.005
		(0.622)		(1.450)
Ln Landfall Distance	-0.135	-0.0339	-0.690***	-0.680***
	(0.300)	(0.196)	(0.144)	(0.149)
Constant	592.1***	-17.07**	260.0***	13.88*
	(54.80)	(6.796)	(97.12)	(7.678)
Observations	108	110	95	81
R-squared	0.498	0.446	0.334	0.315

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Dependent Variable: Log Damages.

3.6 Robustness

We present our robustness results in the Appendix. 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, presenting only the results for direct hits. 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), thus the estimated equations are identical. We test the applicability of a cross-equation coefficient restriction, but find the estimated coefficients in the damage and fatalities equations to be statistically different from each other, thereby negating the motivation of imposing equality. This makes theoretical sense as storm and human factors may both impact damage and fatalities in different and independent ways. Therefore, we leave further exploration of the SUR model, using different explanatory variables for damages and fatalities, as important future work. We also provide additional income bins and estimate income elasticities of damage and fatalities across twelve levels of development. Across all of our robustness checks, we confirm the conclusions of our main empirical results.

We additionally test the impact of national versus subnational data in calculating elasticities. Relying on storms that struck large countries, we compare the results using vulnerability measures (income and population density) at the national scale versus the county scale in the Appendix. National socioeconomic data allows us to identify the broad differences across levels of economic development and federal policies. County-level data sheds light on differences in local vulnerability and adaptation across the same storms. Details of the results are discussed in the Appendix, but broadly, our results suggest that there is more adaptation at the national scale rather than the local scale, highlighting the importance of our subnational data.

Finally, the Appendix presents additional calculations mentioned in the paper. We provide the results of our capital formation assumption, showing that capital scales linearly with changes in income and population. We present the fatality results comparing the United States to the rest of the world and to just other OECD nations.

4 Conclusion

This paper develops a theory of adaptation to tropical cyclone damage and fatalities in order to test for the presence of adaptation. The theory provides several new ways to test for adaptation by comparing empirical parameters of damage and fatality regressions against hypothetical parameter values one might expect if there was no adaptation. We also test hypotheses raised in the literature concerning the adaptation response by areas that are more frequently threatened.

We then conduct an empirical analysis based on a new spatially-explicit historical dataset of more than 1,400 storms that have caused serious damage or lives lost over the last 50 years. We match the damage and fatalities of each storm with the cyclone characteristics at landfall and the characteristics of the impacted local area struck. A set of multiple regressions are then estimated with this new dataset to test for adaptation. Several 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. Second, we look at fatalities and explore whether the elasticity of income is negative and whether the elasticity of population density is less than unitary. Third, we test if there is a negative relationship between impacts and the underlying storm frequency. We decompose these main findings into adaptation across levels of development and urbanization. The primary evidence of adaptation lies in the income and population density results. There is also evidence of a small adaptation effect with respect to frequency. The actual damage and fatalities are much less than potential damage and fatalities as if no adaptation measures were being undertaken.

There are useful policy insights from these results. Most of the world appears to have taken effective precautions to reduce fatalities. Overall, fatalities from tropical cyclones have fallen over time, suggesting an increasingly effective adaptation. As incomes rise, fatalities fall. As population density increases fatalities do not increase proportionally. Places with more frequent high intensity storms manage to reduce fatalities. Unfortunately, places with more frequent low intensity storms have slightly higher fatalities per storm. It is not clear why fatalities per storm would increase with common storms. Perhaps there is a failure in the warning system for low intensity storms. There are also indications that life saving techniques have not permeated everywhere. Over the last two decades, Myanmar and Bangladesh are responsible for 77 percent of the global fatalities from tropical cyclones.[17]

There are also powerful results on the damage from tropical cyclones. The results strongly suggest that higher income increase adaptation. As incomes rise, damage does not rise proportionally. 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. The damage even falls with higher incomes amongst the OECD countries (except the United States). There is also strong evidence that per

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

capita damage is much lower in urban areas. To the extent that development increases both incomes and urbanization, these factors will help reduce the future damage from storms. Development encourages adaptation to natural disasters.

This research reveals adaptation to tropical cyclones is ongoing in most of the world and 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 institutional adjustments such as land use planning? Very little is known about the distribution of damage within a tropical cyclone. Where is the damage concentrated? How far inland do effects spread? What other characteristics of a storm besides frequency and intensity may be important? What best explains the vulnerability of a location?

The analysis reveals important insight concerning publicly available data. Available climatological information about tropical cyclones has substantially improved largely because of the ability of satellites to track and measure storms across the planet. However, the data about damage remains poor. First, EMDAT does a remarkable job of reporting the damage of global tropical cyclones but they have a very small budget given their global task. Second, there is no consistent methodology to measure storm damage. Some countries use replacement costs for old buildings, others use insurance payments to quantify losses. Third, spatially detailed measures of damage across local places struck by storms are not collected. The absence of this data makes it difficult to assess what features of each storm cause damage (winds, storm surge, precipitation, size, or speed). It is also difficult to determine what makes each area and each structure vulnerable. Why is damage higher in one place versus another within an impacted zone? If society wishes to asses what specific adaptations need to be undertaken, it will need more spatially precise damage measurements.

One final insight concerns the damage function of the United States versus the rest of the world. Since 1990, the United States has been responsible for 60% of global tropical cyclone damage even though it is struck by only 4% of global storms.[18] The reason appears to be the damage function of the United States. The income elasticity in the United States is unitary (the income elasticity in all other countries is less than one). This result implies there is no adaptation in the United States. The constant term and the elasticity with respect to intensity are also significantly higher than in other countries. Applying these different coefficients to past storms, the American damage function leads to fourteen times the damage of other OECD countries. These curious results deserve additional research. Are these effects because of a missing variable suggesting much greater vulnerability in the United States? Or do these results suggest there is something very wrong with American public policy that is somehow suppressing adaptation and in-

[18] If we remove Hurricane Katrina from this statistic, the United States represents 50.7% of observed damages in our dataset.

stead encouraging American assets to be in harm's way? Do the subsidized public flood insurance, state caps on coastal insurance rates, and the generous emergency relief programs of the United States combine to reduce the incentive to adapt in America? Whatever is causing American damage to be so much higher than the rest of the world is causing extraordinary damage along the Atlantic and Gulf coasts of the country.

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