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ORIGINAL PAPER

The Impact of Disaster Data on Estimating Damage Determinants and Climate Costs

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Abstract An active literature utilizes natural disaster data to analyze damage determinants and estimate future costs of climate change. However, despite its importance in research and policy, no international standard exists to quantify damages, and the impact of damage data quality on empirical estimates remains an open question. Using the case of tropical cyclone landfalls in China, we analyze three damage datasets: official Chinese government records, CRED's International Disaster Database, and Munich Re's NatCatSERVICE. We begin by systematically comparing damage entries across the three datasets. We then use the data to estimate historical damage functions. Lastly, we utilize the damage functions to project the future costs of climate and economic change. We find that damage data quality matters. While the estimated economic determinants of historical damage functions are similar across the three datasets, we estimate differences in the cyclone intensity coefficients. These variations in damage functions lead to divergence in projections of future damages by almost three times, with average annual future loss estimates ranging between $4 and $11 billion. Similar to previous literature, we call for more internationally standardized disaster damage reporting.

Keywords Data Quality · Natural Disasters · Tropical Cyclones · Climate Change · Integrated Assessment Model

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Introduction

Tropical cyclones cause significant losses to human communities around the globe, averaging $26 billion per year in direct damages, and these losses are expected to increase over the coming century due to changes in climate and human communities (Mendelsohn et al. 2012). With approximately seven landfalls per year in modern history, China experiences significant typhoon losses due both to the high frequency of powerful storms making landfall in this active typhoon-producing basin, as well as economically important population centers located in high risk coastal areas (Gao et al. 1999; Liu et al. 2001). Major recent events have proven fatal and costly. In 2006, Tropical Storm Bilis made landfall in the Fujian province and, despite relatively weak wind speeds and more than two million evacuations, the typhoon led to more than 650 fatalities and almost 35 billion yuan of direct damages (China Ocean Statistics Yearbook 2007; Zhang et al. 2009). The 2009 Typhoon Morakot led to more than 1250 mm of rainfall across some regions of China and affected almost 14.5 million people, resulting in direct economic losses of approximately 12.75 billion yuan (Zhao et al. 2011). In addition, Super Typhoon Herb of 1996, with its powerful Category 5 wind speeds, caused some of the highest direct damages ever experienced in the country, with more than 73 billion yuan lost (Zhang et al. 2009).

Motivated by these environmental threats, growing academic research assesses key policy questions, which include estimating direct determinants of fatalities (e.g., Kahn 2005; Neumayer and Plümper 2007) and damages (e.g., Kellenberg and Mobarak 2008; Kreibich et al. 2014), trends in disaster losses over time (e.g., Brooks and Doswell 2001; Pielke et al. 2008; Neumayer and Barthel 2011), as well as evidence of adaptation across the globe (e.g., Schumacher and Strobl 2011; Hsiang and Narita 2012; Fankhauser and McDermott 2014; Bakkensen and Mendelsohn 2016; Geiger et al. 2016). Modeling disaster damages remains a cornerstone of this line of research and fundamental to the task is accurate damage data. Despite its importance, damage data has been criticized for its lack of systematic accounting standards leading to missing observations, measurement error, and potential strategic reporting (Albala-Bertrand 1993; Drury et al. 2005; Hsiang and Narita 2012; Smith and Katz 2013), all of which can affect empirical identification.[1] However, the impact of damage data quality on empirical estimates remains an open question.

In this paper, we analyze the impact of disaster data quality on empirical estimates of damage determinants and projections of future damages under climate change. We collect damage reports from tropical cyclone landfalls across mainland China found in three commonly utilized data sources: official Chinese government reports, publicly available figures from the International Disaster Database (EM-DAT) of the Centre for Research on the Epidemiology of Disasters, and Munich Re's proprietary NatCatSERVICE records. We begin by comparing individual damage data estimates across the datasets through descriptive statistics in the spirit of Guha-Sapir and Below (2002).[2] We then utilize the three damages datasets to assess the impact

[1] We note that in 2007, CRED and Munich Re spearheaded the "Disaster Category Classification and Peril Terminology for Operational Databases" that lays out common disaster definitions and terminology but an international standard does not yet exist (Wirtz et al. 2014).

[2] See Section 2 for a description of Guha-Sapir and Below's analysis. Our data analysis differs from Guha-Sapir and Below in several ways. We assess a different country context (China). We also include China government data in addition to EM-DAT and Munich Re data (but not Swiss Re), which will allow for comparisons across an official government source. Finally, we originally contribute to the literature through our analysis of damages function and climate and economic change cost sensitivity to underlying damage data quality. Guha-Sapir and Below focus solely on comparisons across the historical observations.

of data quality on historical damage functions and the estimated costs of climate change, heretofore an unexplored question. To do so, we create historical damage datasets, matching damage figures with local cyclone characteristics and economic data to examine the sensitivity of damage function results to variation in underlying damage data. We then utilize a Tropical Cyclone Integrated Assessment Model (Mendelsohn et al. 2012) to estimate resulting sensitivity in the estimated costs of climate and economic change driven by damage data.

We find systematic differences as well as similarities across the three datasets. While official Chinese government data records the largest mean annual losses and contains the most observations, we find interesting similarity across EM-DAT and Munich Re where 52% of reported damages from both databases were within 10% of each other.[3] Turning to our historical regression results, we find key differences in the estimated damage functions driven by the underling damage data. While the estimated coefficients on economic variables (GDP, assets) are strikingly consistent across the damage functions, we find disagreement across the intensity coefficients. Lastly, these differences in damage data – and resulting damage functions - lead to variation in estimated aggregate future damages by almost three times, with average annual future losses ranging between \$4 billion (EM-DAT data) and \$11 billion (China government data). Thus, we find empirical results to be sensitive to underlying damage data. Similar to previous literature (e.g., National Research Council 1999), we call for more transparent and internationally standardized disaster damage reporting. In the meantime, care should be taken when using disaster data, and debates around disaster losses and the costs of climate change should consider disaster data as an important factor in the resulting estimates.

The paper proceeds as follows: we review relevant literature in Section 2. In Section 3, we present the three parts of our empirical approach, including descriptive statistics, historical damages functions, and climate change extension, as well as a description of our data. Section 4 presents and discusses our results. We conclude in Section 5.

Literature

An active and growing literature estimates the direct costs of natural disasters such as tropical cyclones (i.e., hurricanes, typhoons), earthquakes, and floods (see review papers by Cavallo and Noy 2011; Kellenberg and Mobarak 2011; as well as Kousky 2014). Common questions include estimating direct determinants of fatalities (e.g., Kahn 2005; Neumayer and Plümper 2007) and damages (e.g., Kellenberg and Mobarak 2008; Kreibich et al. 2014), trends in disaster losses over time (e.g., Brooks and Doswell 2001; Pielke et al. 2008; Neumayer and Barthel 2011), as well as evidence of adaptation across the globe (e.g., Schumacher and Strobl 2011; Hsiang and Narita 2012; Fankhauser and McDermott 2014; Bakkensen and Mendelsohn 2016; Geiger et al. 2016). In addition, an active literature analyzes the impact of cyclones and other natural disasters on economic growth (e.g., Skidmore and Toya 2002; Noy 2009; Strobl 2011; Hsiang and Jina 2014). Looking ahead, it is well acknowledged that climate change will impact the frequency and intensity of tropical cyclones heterogeneously across the globe (Emanuel 2008; Knutson et al. 2010). As such, a growing literature estimates the potential costs of climate change (Hallegatte 2007; Narita et al. 2009; Nordhaus 2010; Mendelsohn et al. 2012; and see review by Ranson et al. 2014).

[3] This statistic is calculated on a subset of the datasets that could be matched across datasets. See Section 3.1 for a description of the matching process.

Specific to China, Elliott et al. (2015) analyze the effects of typhoons on local economic activity through the use of nightlight luminosity data and detailed wind field reconstructions, finding local economic activity losses – separate from direct damages - to be approximately $1.6 billion per year historically. Assessing direct damages, Chen et al. (2009) estimate detailed damage functions, incorporating precipitation, winds, and intensity to explain various outcomes including property and farmland losses. Zhang et al. (2009) find damages in China to average 28.7 billion yuan per year (in current 2006 yuan; approximately $3.83 billion in real 2009 $USD) utilizing historical official Chinese government data. They conclude that the observed upward trend in damages is explained by increases in economic factors, and not by changing typhoon characteristics. Zhang et al. (2011) note that annual direct damages represent a decreasing fraction of Chinese GDP over time, indicating increased adaptation. Lastly, Gao et al. (1999) analyze the typhoon record from 1949 to 1996, finding an average of 6.6 typhoon landfalls per year, with the south coastal provinces hardest hit based both on frequency and intensity of landfalls. Additional Chinese language literature assesses typhoon risks and impacts (e.g., Cao et al. 2006; Meng et al. 2007; Wang et al. 2007; Xu et al. 2009; Niu et al. 2011).

Concern over damage data quality is not new to the literature (e.g., Albala-Bertrand 1993). Insured loss data are often a cornerstone of damage estimates as insurance companies have incentive to verify losses before claims payouts. Insured losses are often scaled up based on insurance penetration to estimate total direct losses (Smith and Katz 2013) and resulting damage estimates are typically considered high quality. However, natural disaster insurance penetration remains low, especially in developing countries (Linnerooth-Bayer et al. 2011). In 2016, disaster insurance, including both private and public sources across the globe, covered only an estimated 26% of economic losses (Aon Benfield 2016). Thus, the comparative advantage of insurance data relative to other sources is not absolute. In addition, it is unclear that insured losses are systematically similar to, and therefore generalizable to, uninsured losses. Other alternatives include official government data, which is theoretically advantageous since the governing body has firsthand knowledge of disaster impacts, but has been criticized for suffering from strategic manipulation for political goals, such as to increase international aid or appear better able to handle disasters (Albala-Bertrand 1993). Lastly, publicly available data, such as the Centre for Research on the Epidemiology of Disasters' International Disaster Database (EM-DAT), is a third alternative. However, these datasets have been criticized for missing observations and damage reports over time (e.g., Skidmore and Toya 2002; Gall et al. 2009; Hsiang and Narita 2012). Thus, arguably no data source is recognized as "best" and researchers are often left collecting and relying on datasets that are accessible and convenient.

In response, small but growing literature has undertaken careful analyses of systematic differences across disaster dataset observations.[4] Smith and Matthews (2015) assess data quality in the United States. Comparing global sources, Guha-Sapir and Below (2002) assess the quality and accuracy of disaster damage observations in EM-DAT and two insurance datasets (Munich Re and Swiss Re) for Honduras, India, Mozambique, and Vietnam. They find that of the 462 disasters that occurred, 26% were found as entries in all three datasets. In addition, EM-DAT was the most complete for reporting deaths, injuries, and homelessness. Across the four countries studied, damages were unreported for between 67 and 71% of observations in the three datasets. Lastly, they find similarities in damages across the three datasets. Across the subset of entries common to all three sources, only 35% of individual event damage magnitudes are more than 20% apart while 59% of entries are exact matches.

[4] Concern over dataset differences is not unique to cyclone damages. For example, literature assesses differences in cyclone observations across meteorological centers (e.g., Yu et al. 2007; Liang et al. 2010).

Additional literature offers best practices for utilizing the data, given known data limitations. Gall et al. (2009) note common fallacies surrounding disaster data, including the lack of data comparability over time, the potential for minimum thresholds, missing loss types that lead to downwardly biased numbers, and systematic differences across disaster databases. A call in the literature exists for clearer and more systematic damage data collection (National Research Council 1999). Lastly, damage data in China is arguably particularly interesting, given historical concerns about data quality in official government data (Holz 2004) including fertility (Zhang and Zhao 2006), energy (Sinton 2001), GDP (Rawski 2001; Koch-Weser 2013), and environmental indicators (Hsu et al. 2012). However, the extent to which differences in historical and future damage analysis results are driven by differences in underlying damage data quality remains an open question.

Empirical Approach

We conduct our empirical analysis in three parts. We first analyze descriptive statistics and compare individual hand-matched observations across official Chinese government reports (China Gov), Centre for Research on the Epidemiology of Disasters' International Disaster Database (EM-DAT), and Munich Re's NatCatSERVICE (Munich Re). Second, we use the data to estimate historical damage functions in order to test the sensitivity of the regression results to the underlying damage data. To do so, we match damage observations with economic and cyclone data at the point of landfall to estimate historical damage functions. We then test for systematic differences across the resulting magnitudes of estimated coefficients. Lastly, we use the results of our damage functions in a Tropical Cyclone Integrated Assessment Model to estimate the impact of damage data quality on projections of future losses under economic and climate change. Since data are central to our analysis, they will be described in tandem with our empirical approach below instead of in a separate section.

Damage Data and Descriptive Statistics

We begin by describing the three damage datasets and then detail our descriptive statistical analysis. We collect official Chinese government damage estimates at the province level from the Chinese National Meteorology Bureau's China Meteorological Yearbooks. Following a cyclone landfall, the National Meteorology Bureau and Ministry of Civil Affairs collect and compile damage reports from local governments for cyclones with wind speed of at least 17.2 meters per second and for events with direct damages of at least 100 million yuan or at least 10 fatalities. In total, we collected 139 landfalls from 1991 to 2012, as reports before 1991 do not include damage estimates. These direct damage estimates include direct losses from property and infrastructure including cropland. Generally, concern over official government damage data can arise from potential strategic interests of governments to overstate losses, for example to better leverage international aid, or understate damages, for example to appear better adapted (Albala-Bertrand 1993). However, literature is thin with respect to strategic incentives for potential disaster data manipulation in China.

Second, we collect cyclone damage estimates from EM-DAT, the International Disaster Database managed by the Centre for Research on the Epidemiology of Disasters. This dataset is the largest publicly available natural disaster database - with events back to 1900 - and is commonly used in academic research. While EM-DAT collects damage data from multiple sources including official government records, United Nations, and international NGOs, their algorithm for estimating the final damage numbers is not transparent. In addition, EM-DAT has minimum criteria for inclusion relating to fatalities, people affected, declarations of emergency or calls for international assistance. Thus, it is possible that some damaging events are excluded if they did not trigger at least one of the four inclusion criteria. Concern over data quality in EM-DAT, especially regarding missing observations and the quality of recorded damage data (e.g., Skidmore and Toya 2002; Gall et al. 2009; Hsiang and Narita 2012) is common in the literature. Similar to the China government data, EM-DAT also records fatalities, but we do not analyze them in this paper.

Lastly, we collect damage data estimates from the global reinsurance company, Munich Re. NatCatSERVICE, Munich Re's historical disaster damages database, is arguably the largest global disaster damage database, even relative to Swiss Re's Sigma database, in part because events are included if any property damage occurs (Guha-Sapir and Below 2002). However, while it includes historical events as far back as the eruption of Mount Vesuvius in AD 79 and approximately 1000 events are added annually (Munich Re 2017), complete coverage began in earnest in 1980 so the timescale is arguably more limited than EM-DAT (Guha-Sapir and Below 2002), although longer than official China government records. In addition, Munich Re's algorithm for estimating total disaster losses is not publicly available, nor is their event-level database.[5]

For our descriptive statistical analysis, we first convert all event-level damage estimates into real 2009 $USD using currency conversion rates from the World Bank and GDP deflator from the U.S. Bureau of Economic Analysis. We generate annual summary statistics to compare year-by-year figures. We then hand match individual cyclone landfall observations across the three datasets based on observable characteristics including (when available) landfall year, month, location (province), and storm name. If more than one storm is a potential match across the datasets, we employ a conservative approach and do not consider the observations as a match. We also do not match based on the relative damage magnitudes in order not to bias the matches.

From these data, we then generate basic summary statistics and use t-tests to estimate if the correlation coefficients are statistically different. These descriptive statistics will assess any systematic differences across the three datasets. In addition, the results will suggest potential differences across the datasets and will inform our estimates of historical damage functions and costs of climate change. However, because we do not know the "true" damages, we do not conclude that one dataset is more accurate than another.

Historical Damage Functions

After performing descriptive statistics on the datasets, the second part of our analysis assesses the impact of underlying damage data on damage determinants. To do so, we estimate three identical damage function models, varying only by underlying damage estimates across the three damage datasets. We create historical damage datasets using the following steps, such that any difference in regression results will be driven by differences in the magnitudes of damages across damage datasets as well as differences in the underlying samples.[6] We match

[5] We were granted special access to the event-level data for typhoons in China for this study.

[6] Recall that differences in the underlying sample can be driven by different damage estimates as well as any missing data, either from incompleteness or due to events not meeting inclusion criteria, which may vary across damage datasets.

damage data with cyclone landfall characteristics (pressure, wind speed, rainfall, and temperature) and economic data (GDP and exposed assets) as well as the underlying cyclone risk rate.

To construct our estimation datasets, we first use ArcGIS to intersect tropical cyclone tracks from the International Best Track Archive for Climate Stewardship (IBTrACS; Knapp et al. 2010) with Chinese provinces using map layers from the Yale University Map Department in order to associate each cyclone with its minimum sea level pressure and wind speed at landfall. We also use the IBTrACS data to generate province-specific (time-invariant) cyclone risk rates, calculated as the average annual count of cyclone landfalls in a given province. Second, we match, by hand, each observation from the respective damage datasets with cyclone tracks based on (when available) the year, month, province of landfall, and cyclone name. Lastly, we affiliate province-year (of landfall) level GDP (2009 $USD) Chinese National Bureau of Statistics from 1990–2012 as well as typhoon wind-field specific exposed assets estimated by Geiger et al. (2017a, b).[7] We trend province-level GDP back to 1980 using national growth rates. For sensitivity, we also include country-level GDP data from the World Bank and county-level data from Chinese census records.[8] Lastly, using monthly weather station level data from the Chinese government, we affiliate the maximum observed rainfall and temperature from the month and province of cyclone landfall to complete our datasets. We note that while some datasets include extra data, such as wind speed in the Munich Re reports, for consistency in data processing and database creation, we do not use the additional information. In addition, for typhoons that impact multiple provinces, we affiliate the damage data with typhoon and economic data at the province of landfall. All together, we have 139 observations from China Gov (1991–2012), 103 observations from EM-DAT (1980–2012),[9] and 214 observations from Munich Re (1982–2013).

We separately estimate the historical damage functions shown in Eq. 1 using Ordinary Least Squares on each of the three damages datasets. We explain damages at province i and time t using two broad determinants of disaster damages (see Bakkensen and Mendelsohn 2016): economic factors (GDP_{it}), operationalized as province-level GDP as well as cyclone wind field exposed assets, and storm intensity (TC_{it}), operationalized as cyclone maximum wind speed (knots), minimum sea level pressure (mbar), rainfall (mm), and underlying cyclone risk (average annual count per year) at landfall. For sensitivity, we also test GDP at the country and county level, and GDP per capita and population density in lieu of GDP. In additional robustness, we also include monthly temperature (°C) as a control variable. We also estimate results with and without both province (α_i) and decade (δ_t) fixed effects.

$$ln\ Damage_{it} = \gamma + \beta\ ln\ GDP_{it} + \lambda\ ln\ TC_{it} + \alpha_i + \delta_t + u_{it} \tag{1}$$

Given the log-log functional form, we interpret the estimated coefficients as elasticities. The estimated β coefficient informs how damages scale with economic growth. Previous literature (for example, Hsiang and Narita 2012; Nordhaus 2010; Pielke et al. 2008; Pielke and Landsea 1998) has assumed that damages scale proportionately with GDP ($\beta = 1$). However, recent

[7] If more than one province in affected, we use the GDP for the province of typhoon eyewall landfall.

[8] We collect year 2000 county data and assume that the county to country GDP ratio is fixed over time to estimate county-level GDP for our full sample.

[9] The EM-DAT database extends back to 1900 although we only select observations post 1979 for consistency with the other datasets.

work has found while this is true for the United States, much of the world has an estimated coefficient less than 1 ($\beta < 1$), suggesting evidence of adaptation (Bakkensen and Mendelsohn 2016). In addition, debate surrounds the correct cyclone intensity elasticity (λ) with scholars (Emanuel 2005; Bell et al. 2000; Pielke and Landsea 1999) originally assuming damages scaled to the second or third power of wind speed ($\lambda = 2$ or 3), whereas recent work found heterogeneity with higher elasticities of 5 (Bakkensen and Mendelsohn 2016) or even 9 (Nordhaus 2010) in the United States. Thus, our analysis also provides insight into the impact of damage data quality on both debates.

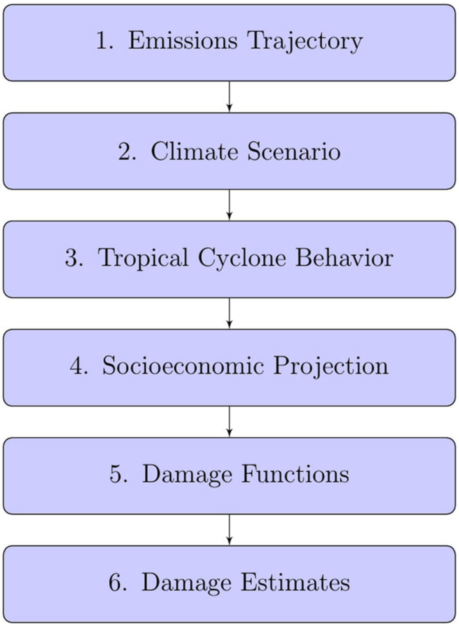
Tropical Cyclone Integrated Assessment Model

Lastly, we use the damages functions estimated in Eq. 1 above in a Tropical Cyclone Integrated Assessment Model (TCIAM) to project the levels of future (year 2100) damages across China using the three damage models. This model was first developed for extreme events in general by Mendelsohn and Saher (2011) and refined by Mendelsohn et al. (2012) for tropical cyclones. Figure 1 below shows the six steps of the TCIAM. Steps 1 through 3 directly follow Mendelsohn et al. (2012). Steps 4, 5, and 6 parallel their analysis, but are applied in a more spatially-refined analysis for China instead of the globe and utilizes the three data datasets.

The first step of the TCIAM fixes an emissions trajectory. For the purposes of this analysis, we use the IPCC SRES A1B emissions path, assuming carbon dioxide equivalent concentrations will stabilize at 720 ppm by the year 2100 and with a storyline of convergent and balanced economic growth with a mix of both fossil fuel and renewable energy sources (Nakicenovic et al. 2000).

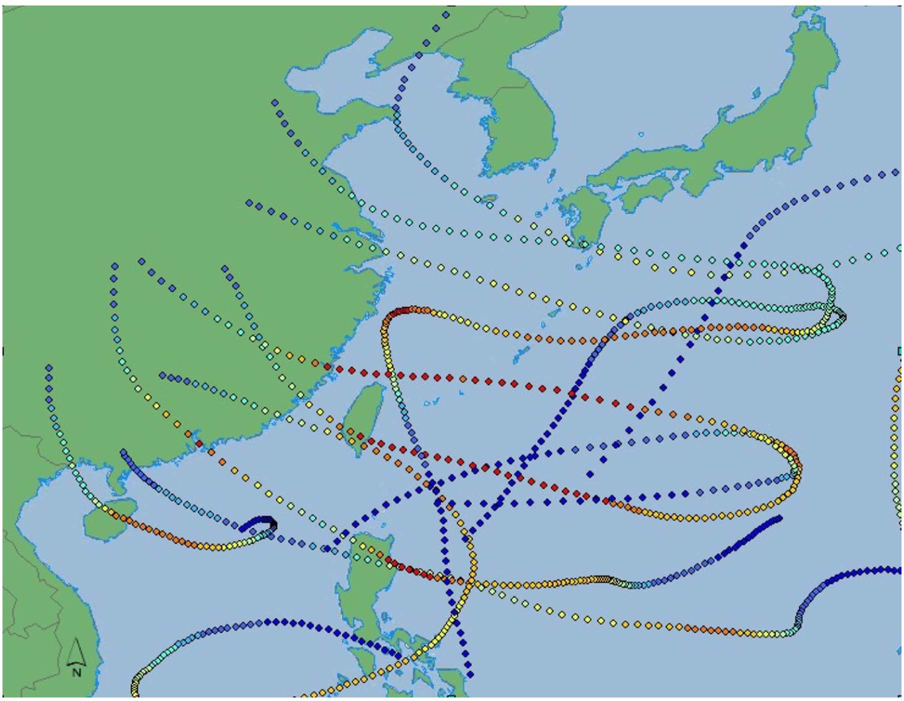
Step two utilizes general circulation models to translate the emissions trajectory into climate outcomes. Similar to Mendelsohn et al. (2012), we employ four climate models: Centre National de Recherche Meteorologiques version CM3 (CNRM; Gueremy et al. 2005), European Centre for

Fig. 1 Tropical cyclone integrated assessment model



Medium Range Weather Forecasts-Hamburg version 5 (ECHAM; Cubasch et al. 1997), Geophysical Fluid Dynamics Laboratory version CM2.0 (GFDL; Manabe et al. 1991) and Model for Interdisciplinary Research on Climate version 3.2 (MIROC; Hasumi and Emori 2004). Each climate model predicts a different change in mean surface temperature. Outputs range across the likely warming estimated by the IPCC, with mean predicted increases of 2.9 °C for CNRM, 3.4 °C for ECHAM, 2.7 °C for GFDL, and 4.5 °C for MIROC (Mendelsohn et al. 2012).

In the third step, we translate climate change into tropical cyclone behavior. While some general circulation models have the spatial resolution adequately fine to resolve hurricanes (Gualdi et al. 2008; Hasegawa and Emori 2005; Knutson and Tuleya 2004), many are currently still too coarse. Thus, we turn to simulated cyclone track output from Emanuel et al. (2008) hurricane generating model. In the model, simulated storm seeds are planted in a modeled ocean. If a storm develops, the subsequent track positions and characteristics, including latitude, longitude, pressure, and wind speed, are recorded similar to the historical record. These tracks are identical to the Western Pacific Ocean tracks utilized in Mendelsohn et al. (2012), including 3000 simulated storms in both current (1980–2000) and future (2080–2100) climate for each of the four climate models, totaling 24,000 simulated tracks. See ten example simulated storm tracks making landfall in China in Fig. 2. In addition, we use the simulation data to estimate changes in the underlying frequency of landfalls at the province level specific to each climate model. Lastly, we assume that typhoon rainfall will be held constant over time. In additional sensitivity, we draw from existing literature (Wang et al. 2012) and assume a 5% increase in typhoon rainfall. We also estimate a parsimonious model without rainfall or underlying frequency as a baseline comparison.



Note: Tracks are colored based on the intensity (minimum sea level pressure) of a storm across the simulated track and recorded every two hours. Red indicates higher intensity and blue indicates lower intensity.

Fig. 2 Example simulated storm tracks by intensity

Step 4 projects the future state of China's population and economy. The IPCC A1B emissions trajectory assumes that global population will be 7.1 billion and world Gross Domestic Product will be $529 trillion in the year 2100 (Nakicenovic et al. 2000) but country-level projections are not included. Thus, we use three Shared Socioeconomic Pathways (SSPs; we utilize paths 1: sustainable path, 2: middle of the road path, and 3: fragmented path), developed to offer a common set of socioeconomic projections at the country and regional levels that are consistent with the SRES emissions scenarios (O'Neill et al. 2012). Since we utilize province-level data, we assume that each province's share relative to China as a whole remains constant over time.[10] However, we are able to capture broad changes in levels of cyclone adaptation over time through both the cyclone risk rate variable and the GDP variable on our damage functions. As a region suffers more cyclones, the cyclone risk rate variable will allow for long term responses to mitigate losses. In addition, the GDP variable will allow damages and adaptation to scale with economic activity.

In the fifth step, we use the three estimated damage functions from Section 3.2 to simulate damages for each simulated track landfall in mainland China. Step six estimates future cyclone damages. Holding climate constant (utilizing only the "current" climate simulation tracks), we first change the economic conditions through the storylines in Step 4. We then calculate the impact of economic changes from 2000 to 2100 on cyclone damages. Lastly in the sixth step and assuming that GDP is fixed at the projected year 2100 levels, we vary climate (utilizing the "future" climate simulation tracks) to calculate the impact of climate change on cyclone damages in China. Using this approach, we can separately estimate the impact of changes to cyclones and the economy, as well as estimate future cyclone losses in the more realistic context of the future, and not current, Chinese economy.

Results and Discussion

In this section, we present our results including descriptive statistical comparisons of the three damage datasets, historical damage functions, and integrated assessment model results.

Damage Data Descriptive Statistics

We begin by comparing the three damage datasets. Recall that we have 139 observations from China Gov (1991–2012), 103 observations from EM-DAT (1980–2012), and 214 observations from Munich Re (1982–2013). We find the China Gov dataset to have the most cyclones recorded from 1991–2012 with 139 observations while Munich Re contains 124 and EM-DAT contains 79 during the same period (including observations with no recorded damages). Table 1 presents summary statistics on average annual damages from cyclones in China from 1991–2008.[11] We find that the China Government data exhibits the largest damage range, with the highest mean annual damages, largest standard deviation, as well as largest minimum and maximum values. This is consistent with the fact that China includes the most observations in their records and therefore, all else equal, should contain higher annual-level statistics. Finally,

[10] For example, if a province has a population density 20% higher than China as a whole, we assume it remains 20% more dense relative to China as a whole over the coming century.

[11] We do not present statistics on individual cyclone-landfall damages due to our confidentiality agreement with Munich Re.

Table 1 Summary statistics for annual cyclone damages (1991–2008, $ billions 2009 USD)

	Munich Re	China Gov	EM-DAT
Mean	1.82	2.88	2.30
St Dev	1.94	2.48	2.37
Minimum	0.01	0.11	0.00
Maximum	6.38	9.02	7.99

Note that in 2002, EM-DAT recorded one unnamed cyclone landfall in China but damages are not recorded. We record this observation as a zero here but throughout the analysis, any observations with missing damage data are dropped from the analysis. Other than 2002, the minimum damage year observed in the EM-DAT data is 1995 with $0.11 billion in damages.

we find variation in average mean losses per year, ranging from $1.82 billion in Munich Re to $2.88 billion from official Chinese government records. Comparing with existing literature, Zhang et al. (2009) estimate annual cyclone losses to be $3.83 billion.[12] In addition, although not modeling direct damages, Elliott et al. (2015) estimate annual losses of $1.6 billion from reductions in economic activity due to cyclones.

To assess similarities between average annual damages, we calculate the Pearson's correlation between pairwise annual damage figures and present the results in Table 2. We find the correlations to be different from zero at less than the 0.01% level. Munich Re and EM-DAT damages are most highly correlated ($r = 0.916$). EM-DAT and China Gov data show the lowest correlation across average annual damages ($r = 0.667$).

Finally, we turn to our hand-matched event-level data. We conservatively hand match the data and do not include the match if we are not confident that the records are unique matches and the observation is present across all three datasets. With these criteria, we find 30 matching cyclones across the three datasets, however some have missing damage data in one or more datasets.[13] Thus, we take the event-level data comparisons as interesting but potentially not representative of the entire sample. With that in mind, we find China Gov data to have the greatest range, with both the lowest and highest damages, as well as largest standard deviation, at the per-storm level. Interestingly, while China Gov data has the highest median value, Munich Re has the highest mean value of damages. Lastly, we find important similarity between EM-DAT and Munich Re event-level records. From our matched subset, we find 52% of recorded damage values across Munich Re and EM-DAT to be within 10% of each other. Thus, these two datasets show the largest amount of consistency across damage records, whereas China Gov and EM-DAT damage figures are within 10% only 14% of the time and 19% of the time between China Gov and Munich Re.

Historical Damage Functions

We next utilize the three damage datasets to estimate historical damage functions. As noted in Section 3, we process the damage datasets using identical steps in order to ensure differences in the results are driven by differences across the damages data themselves, and not additional data or assumptions.

[12] Original estimates were 28.7 billion yuan (in 2006 currency) and were converted to real 2009 $USD by the authors.

[13] For comparison, Guha-Sapir and Below (2002) find a 26% match rate across their three datasets.

Table 2 Pairwise correlation between average annual damages

	Munich RE	China Gov	EM-DAT
Munich RE	1		
China Gov	0.717***	1	
EM-DAT	0.916***	0.667***	1

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

In Table 3, we present the results of the historical damage functions without province and decade fixed effects that were generated using minimum sea level pressure as a proxy for cyclone intensity in odd numbered columns, and maximum wind speed in even numbered columns. Columns one through four are estimated using damage data from Munich Re, columns five through eight are estimated using official Chinese government data, and columns nine through twelve are estimated using EM-DAT data. In addition, we use either province or typhoon wind-field GDP, in addition to rainfall and underlying typhoon risk data in all the specifications. We find that across the three datasets, the Chinese government data models have the highest R-squared terms, which explain between 52 and 57% of variation in the model. In addition, this dataset has the largest number of observations at 121. EM-DAT data explains approximately 27% of the variation and also contains the smallest sample.

Turning to the estimated coefficients, recall that they can be interpreted as elasticities given the log-log functional form. We find similarity in the GDP elasticities across the three damage datasets, all between 0.23 and 0.39. We perform an F-test on each of the coefficients, to test if they are different from the values of the other two models, and cannot reject the null hypothesis that they are the same values at the 10% level for the province GDP elasticities.[14] We find some differences across the typhoon wind-field assets estimates, with the EM-DAT column 11 assets coefficient being statistically different from Munich Re. However, all estimated coefficients are less than 1 at the 10% level, indicating that damages do not scale proportionately with economic growth, evidence of adaptation to typhoon risk in China and in contrast to what is assumed by some previous literature (Hsiang and Narita 2012; Nordhaus 2010; Pielke et al. 2008; Pielke and Landsea 1998) or is estimated for the United States (Bakkensen and Mendelsohn 2016). However, the elasticity is still higher than that of non-US OECD countries (Bakkensen and Mendelsohn 2016) and we note that the positive elasticity still implies that aggregate damages will increase with economic growth, all else equal.

For sensitivity, we also estimate the models using country and county level GDP, but find province level GDP to be a better model based on the adjusted R-squared, AIC, and BIC statistics. We also decompose aggregate GDP into population density and GDP per capita (as in Bakkensen and Mendelsohn 2016). However, we find that the estimated coefficients on the economic variables of this specification are not significantly different from zero, perhaps due to the small sample size, and therefore present the GDP coefficients as our main results. Lastly, we also include province-level temperature in the month of typhoon landfall as an explanatory variable but find the estimated coefficient to be insignificant.

[14] We test GDP elasticities across the three wind models and, separately, across the three pressure models.

Table 3 Cross-sectional typhoon historical damages functions using three damages datasets

	(1) Munich Re Ln damages	(2) Munich Re Ln damages	(3) Munich Re Ln damages	(4) Munich Re Ln damages	(5) China Gov Ln damages	(6) China Gov Ln damages	(7) China Gov Ln damages	(8) China Gov Ln damages	(9) EM-DAT Ln damages	(10) EM-DAT Ln damages	(11) EM-DAT Ln damages	(12) EM-DAT Ln damages
Ln province GDP	0.348*	0.396*			0.242**	0.265***			0.231	0.278*		
	(0.203)	(0.201)			(0.106)	(0.0976)			(0.142)	(0.141)		
Ln assets			0.573*	0.536			0.334**	0.253			0.0750	0.246
			(0.331)	(0.329)			(0.160)	(0.157)			(0.115)	(0.204)
Ln MSLP	−57.52***		−46.01***		−79.00***		−71.63***		−7.685		−9.474	
	(13.52)		(15.14)		(9.528)		(10.42)		(14.01)		(16.35)	
Ln wind		4.163***		3.431***		4.737***		4.493***		0.970		1.233
		(0.894)		(1.045)		(0.501)		(0.611)		(1.012)		(1.144)
Ln rain	0.843*	1.005**	0.895**	1.025**	0.433*	0.685***	0.419	0.610**	0.376	0.214	0.540	0.438
	(0.452)	(0.453)	(0.419)	(0.426)	(0.248)	(0.220)	(0.253)	(0.234)	(0.351)	(0.364)	(0.377)	(0.409)
Ln typhoon risk	−0.971***	−0.942***	−0.989***	−0.899***	−0.597**	−0.688***	−0.621**	−0.581**	−0.757**	−0.543*	−0.709**	−0.508*
	(0.361)	(0.354)	(0.341)	(0.332)	(0.234)	(0.207)	(0.254)	(0.230)	(0.317)	(0.320)	(0.295)	(0.303)
Constant	402.0***	−12.97*	316.3***	−14.13*	554.7***	−10.05***	501.6***	−8.568**	64.86	7.589	80.17	5.831
	(94.23)	(7.199)	(108.3)	(7.961)	(66.03)	(3.152)	(73.64)	(3.664)	(96.34)	(5.703)	(113.6)	(7.114)
Observations	99	96	93	90	121	116	111	107	67	60	61	54
R-squared	0.240	0.297	0.279	0.318	0.409	0.489	0.423	0.483	0.112	0.106	0.089	0.094

Robust standard errors in parentheses

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

Regarding the cyclone intensity elasticities, we find strikingly different results. Unlike GDP, estimated intensity elasticities are sensitive to differences in underlying damage data. Considering first the wind elasticities, which previous literature had assumed to be between 2 and 3 (Emanuel 2005; Bell et al. 2000; Pielke and Landsea 1999), we find EM-DAT generates the lowest (and also least significantly) estimated wind elasticity of between 1.9 and 1.2, lower than Munich Re's elasticity of between 3.4 and 4.2, and China Gov's elasticity of 4.5 and 4.7. Similar with the minimum pressure elasticities, albeit negative since a more intense cyclone has a lower pressure reading, we find EM-DAT to have an estimated coefficient smallest (closest to zero) magnitude of between −7.7 and −9.5, although it is not statistically significant. Munich Re data estimates an elasticity of between −46 and −58 while China Gov estimates a super high (negative) elasticity of −71 and −79, very closely in line with the pressure elasticity of −84.75 calculated for the United States by Bakkensen and Mendelsohn (2016).[15] Performing F-tests, we find that EM-DAT estimated intensity coefficients to be statistically different from those of Munich Re and China Gov. Thus, we find evidence that estimated intensity elasticities are sensitive to underlying damage data, which can help inform the wind speed power law debate as well as sensitivity to damages in general.

Lastly, we find that both cyclone precipitation and the underlying cyclone risk to be important determinants of disaster damages. We find the rain elasticity to be between 0.4 and 1.0, highlighting rain as an important and distinct damage channel in addition to wind. Across the datasets, the EM-DAT rain coefficients are the least significant. We also find that underlying typhoon risk matters, with all twelve specifications having negative and significant estimated coefficients. All else equal, areas that are hit more frequently have lower per-event damages, which is additional evidence of adaptation.

Table 4 presents the results for our historical damage functions with province and decade fixed effects included to control for any decade-specific and province-specific factors, and patterns identically after the specifications in Table 3. This specification is identified using within province and decade variation. We note that there are important differences in the interpretation of the estimated coefficients across the cross-sectional results in Table 3 and the fixed effects results of Table 4 (for a broad discussion, see e.g., Timmins and Schlenker 2009; Samuelson 1947). Namely, including fixed effects will control for any long run adaptation that takes place within a province. For example, the typhoon risk variable is subsumed in the fixed effect. Thus, we can interpret these as short run impact responses versus long run responses for the cross-sectional specifications. We note also that the cross-sectional specifications can suffer from omitted variable bias. Therefore, we present both in this section of the paper. However, since the fixed effects may soak up some important long run adaptation channels (see, for example Bakkensen and Barrage 2016), we utilize our cross-sectional results in our Tropical Cyclone Integrated Assessment Model.

We find similarity in the pressure, wind, and rain coefficients across the fixed effects and cross-sectional specifications. For the pressure elasticity, EM-DAT has the lowest coefficient at between 1.3 and 1.6, whereas Munich Re finds damage scale to the 3.7th power of wind while China Gov estimates a power of 4.8. The estimate pressure coefficients reflect the same pattern, with EM-DAT having the smallest (closest to zero) coefficients and China Gov with the largest (most negative) coefficients. However, the EM-DAT estimated coefficients are not statistically different from zero. Similarly, we find rain to be a positive and significant determinant of damages although it is not significant in all EM-DAT specifications. Turning

[15] Bakkensen and Mendelsohn utilize EM-DAT data as well as damage data from Nordhaus (2010).

Table 4 Typhoon historical damages functions using three damages datasets with fixed effects

	(1) Munich Re Ln damages	(2) Munich Re Ln damages	(3) Munich Re Ln damages	(4) Munich Re Ln damages	(5) China Gov Ln damages	(6) China Gov Ln damages	(7) China Gov Ln damages	(8) China Gov Ln damages	(9) EM-DAT Ln damages	(10) EM-DAT Ln damages	(11) EM-DAT Ln damages	(12) EM-DAT Ln damages
Ln province GDP	−0.342	−0.310			−0.0223	−0.0179			0.418*	0.449*		
	(0.299)	(0.299)			(0.198)	(0.156)			(0.247)	(0.256)		
Ln assets			0.203	0.136			0.190	0.0834			−0.0655	0.201
			(0.345)	(0.329)			(0.136)	(0.135)			(0.173)	(0.342)
Ln MSLP	−52.28***		−53.01***		−83.65***		−80.05***		−15.35		−20.03	
	(13.58)		(14.22)		(9.122)		(9.632)		(14.62)		(16.38)	
Ln wind		3.655***		3.750***		4.881***		4.814***		1.254		1.639
		(0.931)		(1.053)		(0.469)		(0.530)		(0.950)		(1.065)
Ln rain	1.034**	1.209***	1.225***	1.375***	0.616***	0.809***	0.597**	0.762***	0.535	0.463	0.762**	0.734*
	(0.407)	(0.402)	(0.425)	(0.427)	(0.230)	(0.205)	(0.242)	(0.218)	(0.378)	(0.384)	(0.371)	(0.391)
Constant	382.9***	6.386	373.0***	−6.316	592.9***	−3.893	562.8***	−5.882	113.2	0.0357	157.3	3.285
	(94.70)	(8.977)	(99.40)	(9.617)	(63.90)	(4.258)	(67.49)	(3.711)	(99.95)	(6.319)	(114.7)	(8.509)
Decade FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	99	96	93	90	121	116	111	107	67	60	61	54
R-squared	0.410	0.454	0.426	0.462	0.519	0.569	0.530	0.571	0.285	0.271	0.282	0.276

Robust standard errors in parentheses

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

to the economic variable, we find the estimated coefficients to be insignificant, except for the two EM-DAT GDP specifications, and inconsistent in terms of magnitudes and signs. This could be due to the province fixed effect soaking up meaningful variation in the economic data. Lastly, we note that the underlying cyclone risk rate is not included as it is does not vary over time in our historical sample and therefore subsumed by the fixed effect. In the Appendix, we also present historical damage function results in a parsimonious specification using only proxies for economic activity and cyclone intensity for both cross sectional and fixed effects specifications and find similar results to those presented here.

Integrated Assessment Models: Climate and Economic Change Impacts

In order to assess the impact of underlying damage data on estimated costs of economic and climate change, we utilize the historical damage functions from Table 3 in a Tropical Cyclone Integrated Assessment Model (TCIAM) to estimate future cyclone damages from both economic growth and climate change.[16] We first estimate the impact of economic growth on cyclone losses in China. Recall that we utilize three Sustained Socioeconomic Pathway (SSP) storylines to estimate future economic conditions in China. SSP1 represents a sustainable path forward with future GDP in China 6.65 times higher than today. SSP2 represents a middle of the road scenario with GDP 6.49 times higher than today. Lastly, SSP3 represents slower, fragmented global growth with future GDP in China 4.05 times higher than today.

Estimates of the impact of economic change on cyclone damage are presented in Table 5. We find qualitative consistency across the three damages datasets, all finding increases in future losses of between about 40 and 110%. As expected, utilizing Munich Re data leads to the largest projections of future damage increases, given the larger GDP elasticity parameters. With average annual losses between \$1.8 and \$2.9 billion per year from 1991–2008, this can lead to a difference in expected average annual damages of more than \$1 billion. We also note that the scenario with the fastest economic growth (SSP1) leads consistently to the highest future damages, given the GDP elasticities are greater than zero. In addition, since the GDP elasticities in the wind-based damage function are slightly larger those of the minimum sea level pressure (MSLP) functions, we find that the losses are larger - by between about 5 to 10 percentage points - in the wind results relative to pressure.

Next, we turn to our climate change results, presented in Table 6. Note that these results assume GDP to be at the SSP2 future level, only varying the climate conditions. As signaled from the historical damage functions, we find large differences in future estimates of climate change losses, especially with respect to the minimum sea level pressure (MSLP) results. This is driven both due to very large MSLP elasticities as well as a larger climate change signal in cyclone characteristics relative to the wind signal. Averaging across the four climate models, we find China Gov damage data to estimate the largest (least negative) changes in future damages of approximately 150% increases in the pressure model. EM-DAT estimates numbers closest to zero, between 6.5 and 14%, across wind and pressure models, respectively. As previous work has found pressure at landfall to be a better damage proxy than wind (Bakkensen and Mendelsohn 2016 as is scientifically motivated by Chavas et al. 2017),

[16] The six TCIAM steps are described in Section 3.3 above.

Table 5 Economic change impact on cyclone damages in China

	China Gov	EM-DAT	Munich RE
SSP1 (MSLP)	58.12%	55.01%	93.77%
SSP2 (MSLP)	57.33%	54.08%	91.38%
SSP3 (MSLP)	40.14%	38.31%	62.72%
SSP1 (Wind)	65.36%	69.26%	111.88%
SSP2 (Wind)	64.10%	68.19%	109.29%
SSP3 (Wind)	45.20%	47.65%	74.11%

Note: These represents the future increase in cyclone losses from current levels in China due to projected changes in GDP from 2010 to 2100, holding climate constant. We vary the underlying damage dataset, as well as future economic scenarios, and damage function cyclone intensity proxy (wind versus minimum sea level pressure) for sensitivity.

focusing on wind may lead to underestimates of future cyclone losses. The results also highlight continued uncertainty in modeling future climate, as shown through the variation across the general circulation model estimates. For example, ECHAM and GFDL both predict average decreases in future losses due to an average weakening of cyclones whereas CRNM and MIROC models predict increasing damages.

Lastly, Table 7 translates our results from Tables 4 and 5 into average (aggregate) annual losses. Estimates of current annual losses (averaged from 1991 to 2008, in real 2009 $USD) range from $1.82 billion per year in the Munich Re database to $2.88 billion per year in the China Gov data. Economic change will increase these losses to between $1.24 (EM-DAT) and $1.99 billion per year (Munich Re). Total future damages are projected to be between $4.04 (EM-DAT, MSLP) and $11.26 billion per year (China Gov, MSLP), almost a threefold difference. Thus, underlying damage data alone can lead to significantly different calculated aggregate costs of climate change. Comparing our results with the existing literature, Mendelsohn et al. (2012) use a global cyclone damage model in their integrated assessment model and estimate future baseline cyclone damage, including economic but not climate change, to be $8 billion per year, with climate change adding an additional $14.7 billion per year. In the Appendix, we present additional results assuming a 5% increase in rainfall and also utilizing our parsimonious (Appendix) specification of historical damage functions.

Table 6 Climate change impact on cyclone damages in China

	China Gov MSLP	EM-DAT MSLP	Munich Re MSLP	China Gov Wind	EM-DAT Wind	Munich Re Wind
CRNM	401.49%	−1.19%	97.81%	9.77%	−3.17%	5.88%
ECHAM	−12.11%	1.11%	−8.41%	−12.97%	−2.61%	−11.50%
GFDL	−98.31%	38.21%	−80.71%	−50.98%	13.46%	−35.84%
MIROC	302.79%	17.97%	174.25%	76.61%	18.30%	77.81%
Average	148.47%	14.03%	45.73%	5.61%	6.50%	9.09%

Note: These represents the future increase in cyclone losses from current levels in China due to changes in climate conditions from the average current climate (from 1980–2000) to future climate (2080–2100), holding GDP fixed at the projected year 2100 levels. We vary the underlying damage dataset, as well as future general circulation model (CRNM, ECHAM, GFDL, and MIROC), and damage function cyclone intensity proxy (wind versus minimum sea level pressure) for sensitivity.

Table 7 Current and future average annual cyclone damages in China ($ Billions)

	China Gov	EM-DAT	Munich Re
Current losses	2.88	2.30	1.82
Future losses with economic change (MSLP)	4.53	3.55	3.49
Total future losses (MSLP)	11.26	4.04	5.08
Future losses with economic change (Wind)	4.73	3.87	3.82
Total future losses (Wind)	4.99	4.12	4.16

Note: These represents total losses (in $ billion in 2009 USD) from cyclone losses in China due to changes in economic conditions from 2010 to 2100, holding climate constant and total future losses including economic change and climate change. We vary the cyclone intensity proxy (wind versus minimum sea level pressure) for sensitivity.

Conclusion

A growing and active literature analyzes natural disaster damages data to estimate determinants of damage, evidence of adaptation, and future projections of climate and economic change impact. Disaster damage data remains a cornerstone of these analyses yet no international accounting standards exist to consistently quantify losses. Using the case of cyclones in China, we analyze three damage datasets: official Chinese government reports, EM-DAT, and Munich Re's NatCatSERVICE dataset. We find important and significant differences across disaster damage datasets and subsequent empirical results. Differences across the three datasets can be driven by differences in the per-event damages recorded as well as differences in the underlying samples including different start dates and criteria for inclusion. Since we do not observe true damages, we do not conclude which dataset is "best" but rather present our results to add context to research and policy decisions based on damage data. Limitations of our research motivate future work. The external validity of our results across other countries remains an open question. In addition, we do not capture storm surge or sea level rise in our integrated assessment model. Similar to previous literature, we echo the call for greater transparency and consistency in damage data collection. Until then, policy makers and researchers should carefully consider damage data quality when assessing disaster impacts as well as creating and evaluating policy to combat them.

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Appendix

Baseline Historical Damage Functions

Table 8 presents our tropical cyclone damages function using a parsimonious baseline specification with only province-level GDP and cyclone intensity (wind or pressure) included as explanatory variables. We find broad similarity across these and the main results damage functions presented in Table 3, with GDP elasticity values of around 0.2 and 0.3. In addition, we find the China Gov intensity elasticities to be the largest (farthest from zero) and the EM-DAT coefficients to be the closest to zero. Table 9 presents the same specification but with decade and province fixed effects. Again, similar to Table 6 in the main results, we find the GDP elasticity to vary in sign and significance across the three datasets. We continue to find China Gov intensity elasticities to be the largest in magnitude and EM-DAT to be closest to zero in magnitude and significance.

Table 8 Baseline typhoon damages functions using three damages datasets

Dataset Dependent variable	(1) Munich Re Ln damage	(2) Munich Re Ln damage	(3) China Ln damage	(4) China Ln damage	(5) EM-DAT Ln damage	(6) EM-DAT Ln damage
Ln province GDP	0.254	0.314*	0.178*	0.201**	0.205*	0.214*
	(0.175)	(0.175)	(0.107)	(0.0982)	(0.116)	(0.118)
Ln MSLP	−46.76***		−78.49***		−8.091	
	(13.24)		(9.621)		(14.21)	
Ln wind		3.384***		4.648***		1.212
		(0.876)		(0.504)		(1.028)
Constant	334.5***	−2.583	554.9***	−4.595	69.92	8.985**
	(92.90)	(5.229)	(66.79)	(2.842)	(98.22)	(4.479)
Decade & province FE?	N	N	N	N	N	N
Observations	115	110	121	116	71	64
R-squared	0.126	0.167	0.382	0.442	0.034	0.072

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 9 Baseline cyclone damages functions with fixed effects using three damages datasets

Dataset Dependent variable	(1) Munich Re Ln damage	(2) Munich Re Ln damage	(3) China Ln damage	(4) China Ln damage	(5) EM-DAT Ln damage	(6) EM-DAT Ln damage
Ln province GDP	−0.261	−0.251	0.0417	0.0677	0.550***	0.500**
	(0.299)	(0.300)	(0.192)	(0.154)	(0.183)	(0.223)
Ln MSLP	−42.33***		−82.28***		−26.93*	
	(13.23)		(9.201)		(15.23)	
Ln wind		2.815***		4.720***		2.092*
		(0.892)		(0.472)		(1.093)
Constant	318.3***	15.25*	585.4***	−0.664	193.2*	−1.959
	(93.40)	(8.099)	(64.34)	(4.255)	(106.2)	(4.954)
Decade & province FE?	Y	Y	Y	Y	Y	Y
Observations	115	110	121	116	71	64
R-squared	0.306	0.323	0.498	0.534	0.282	0.280

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

Integrated Assessment Model Additional Results

To estimate TCIAM sensitivity to model assumptions, we run the TCIAM using two additional base models. In Table 10, we present the results assuming our parsimonious baseline damage functions from Appendix Table 8, including only province-level GDP and cyclone intensity (wind or pressure). We find that without accounting for rain and underlying cyclone risk, the results are slightly lower, with estimated total future losses (MSLP) of between \$3.36 and

\$10.09 billion on average per year, compared to between \$4.04 and \$11.26 billion in our main results. In Table 11, we present results using our main damage function results but assume that cyclone rainfall will increase by 5%, guided by Wang et al. (2012). Logically, holding all else equal and intensifying rainfall, we find that estimated future cyclone losses increase to between \$4.4 and \$12.85 billion. However, these additional estimates are still within approximately 10% of our original estimates, giving confidence in the estimated costs. We also note that the broad qualitative conclusions across all TCIAM runs remains the same, as we find that the EM-DAT model predicts smaller future increases and the China Gov model predicts highest future increases across a majority of the specifications.

Table 10 Current and future average annual cyclone damages in China ($ Billions) assuming baseline damage functions

	China Gov	EM-DAT	Munich Re
Current losses	2.88	2.30	1.82
Future losses with economic change (MSLP)	4.02	3.38	2.93
Total future losses (MSLP)	10.09	3.36	3.39
Future losses with economic change (Wind)	4.20	3.44	3.28
Total future losses (Wind)	4.12	3.35	3.14

Note: These represents total losses (in $ billion in 2009 USD) from cyclone losses in China due to changes in economic conditions from 2010 to 2100, holding climate constant and total future losses including economic change and climate change. We vary the function cyclone intensity proxy (wind versus minimum sea level pressure) for sensitivity.

Table 11 Current and future average annual cyclone damages in China ($ Billions) assuming main results damage functions and 5% increase in cyclone precipitation

	China Gov	EM-DAT	Munich Re
Current losses	2.88	2.30	1.82
Future losses with economic change (MSLP)	4.02	3.38	2.93
Total future losses (MSLP)	12.85	4.53	6.56
Future losses with economic change (Wind)	4.20	3.44	3.28
Total future losses (Wind)	6.14	4.40	5.64

Note: These represents total losses (in $ billion in 2009 USD) from cyclone losses in China due to changes in economic conditions from 2010 to 2100, holding climate constant and total future losses including economic change and climate change. We vary the function cyclone intensity proxy (wind versus minimum sea level pressure) for sensitivity and assume a 5% increase in cyclone rainfall.

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