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An exploration of trends in normalized weather-related catastrophe losses

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Condensed summary

In order to evaluate potential trends in global natural catastrophe losses, it is important to compensate for changes in asset values and exposures over time. We create a Global Normalized Catastrophe Catalogue covering weather-related catastrophe losses in the principal developed (Australia, Canada, Europe, Japan, South Korea, United States) and developing (Caribbean, Central America, China, India, the Philippines) regions of the world. We survey losses from 1950 through 2005, although data availability means that for many regions the record is incomplete for the period before the 1970s even for the largest events. After 1970, when the global record becomes more comprehensive, we find evidence of an annual upward trend for normalized losses of 2% per year. Conclusions are heavily weighted by US losses, and their removal eliminates any statistically significant trend. Large events, such as Hurricane Katrina and China flood losses in the 1990s, also exert a strong impact on trend results. In addition, once national losses are further normalized relative to per capita wealth, the significance of the post-1970 global trend disappears. We find insufficient evidence to claim a statistical relationship between global temperature increase and normalized catastrophe losses.

12.1 Introduction

Economic losses attributed to natural disasters have increased from US$75.5 billion in the 1960s to US$659.9 billion in the 1990s (United Nations Development Programme [UNDP], 2004), for an annual growth rate of approximately 8%. Private sector data also show rising insured losses over a similar period (Munich Re, 2001–; Swiss Re, 2005). Both reinsurers and some climate scientists have argued that these increases demonstrate a link between anthropogenically induced global warming and catastrophe losses

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(Intergovernmental Panel on Climate Change [IPCC], 2001). However, failing to adjust for time-variant economic factors yields loss amounts that are not directly comparable and a pronounced upward trend through time that can be attributed to purely economic factors.

To allow for a comparison of losses over time, previous studies have adjusted past catastrophe losses to account for changes in monetary value in the form of inflation. However, in most countries, far larger changes have resulted from variations in human factors such as wealth and the numbers and values of properties located in the paths of the catastrophes (Van der Vink *et al*., 1998; Changnon *et al*., 2001). A full normalization of losses, which has been undertaken for the US hurricane (Pielke and Landsea, 1998; Collins and Lowe, 2001; National Oceanic and Atmospheric Administration [NOAA], 2005) and flood (Pielke *et al*., 2002), also includes the effects of changes in wealth and population to express losses in constant dollars. These previous national US assessments, as well as those for normalized Cuban hurricane losses (Pielke *et al*., 2003), have failed to show an upward trend in losses over time, but this was for the period before the remarkable US hurricane losses of 2004 and 2005.

In order to assess global trends over time, we compiled a database of normalized economic losses attributed to weather-related catastrophes from 1950 through 2005 from a large and representative sample of geographic regions. Regions were selected that had a reasonable centralization of catastrophe loss information as well as a broad range of peril types: tropical cyclone, extratropical cyclone (windstorm), thunderstorm, hailstorm, tornado, wildfire, and flood. The surveyed regions also span high- and low-latitude areas. Although global in scope, this study does not cover all regions. For example, we did not include losses from Africa or South America – first, because these continents are more affected by persistent climatological catastrophes (in particular, drought) than sudden-onset weather-related catastrophes. Also, the core economic loss data, in particular for much of Africa, were simply unavailable. However, the surveyed area included the large portion of the world's asset exposure and most of its population.

12.2 Data

We compiled economic loss data from international agencies, national databases, insurance trade associations, and reinsurers, as well as from RMS internal figures. Where possible, we tried to locate at least one government source with an official loss estimate. In some of the developing regions, this was not always possible and we deferred to private sector estimates or those provided by international bodies. We actively sought multiple loss estimates for events, and in cases where one event had different loss estimates we used the consensus mean estimate (or the median estimate if more appropriate). In cases where the quality of insured loss data exceeds that of economic losses, we estimated economic losses based upon insurance coverage ratios for the affected region and hazard type from contemporary insurance penetration rates. Data sources used for the normalization calculations are listed in Table 12.1.

Table 12.1. *Data sources used for normalization calculations*

AXCO Insurance Information Services (subscription). www.axcoinfo.com/.
Benson, C., and Clay, Edward J. (2001). Dominica: natural disasters and economic development in a small island state. Disaster Risk Management Working Paper Series No. 2. Washington, D.C.: World Bank.
Central Water Commission, Government of India. http://cwc.nic.in/.
Dartmouth Flood Observatory. www.dartmouth.edu/~floods/index.html.
EM-DAT: The OFDA/CRED International Disaster Database. www.em-dat.net/.
Emergency Management Australia (EMA). www.ema.gov.au/ema/emaDisasters.nsf.
Etkin, David, and Brun, Soren Erik (2001). Canada's hail climatology: 1977–1993. Institute for Catastrophe Loss Reduction Paper Series, No. 14.
Flood Damage in the United States. www.flooddamagedata.org.
General Insurance Association of Japan (GIAJ). www.sonpo.or.jp/e/index.html.
Guangzhou Institute of Geography (2002). *Atlas of Major Disasters and Society Responding to Them in China*. Guangzhou, China: Guangdong Science and Technology Press.
Insurance Bureau of Canada (IBC). Facts of the insurance industry (2004). www.ibc.ca/pdffiles/publications/brochures/consumer/FACTS_E04.pdf.
Insurance Disaster Response Organization (IDRO). www.idro.com.au/disaster_list/default.asp.
International Monetary Fund. International Financial Statistics. CD-ROM.
International Monetary Fund (1998). Letter of intent from Saint Kitts & Nevis. www.imf.org/external/np/loi/121098.htm.
ISO Property Claim Services (subscription). www.iso.com/products/2800/prod2801.html.
Public Safety and Emergency Preparedness Canada. Canadian Disaster Database. ww3.psepc-sppcc.gc.ca/disaster/default.asp.
Shi, P., ed. (2003). *Atlas of Natural Disaster System in China*. Beijing, China: Science Press.
Swiss Reinsurance Company. Annually 1998–2006. Sigma. *Natural Catastrophes and Man-Made Disasters*. Zürich: Swiss Reinsurance Company, Economic Research & Consulting.
United Nations National Accounts Statistics Database. (2006). http://unstats.un.org/unsd/snaama/Introduction.asp.
United Nations World Population Prospects: The 2004 Revision Population Database. http://esa.un.org/unpp/.
United States National Hurricane Center (NHC). www.nhc.noaa.gov/.

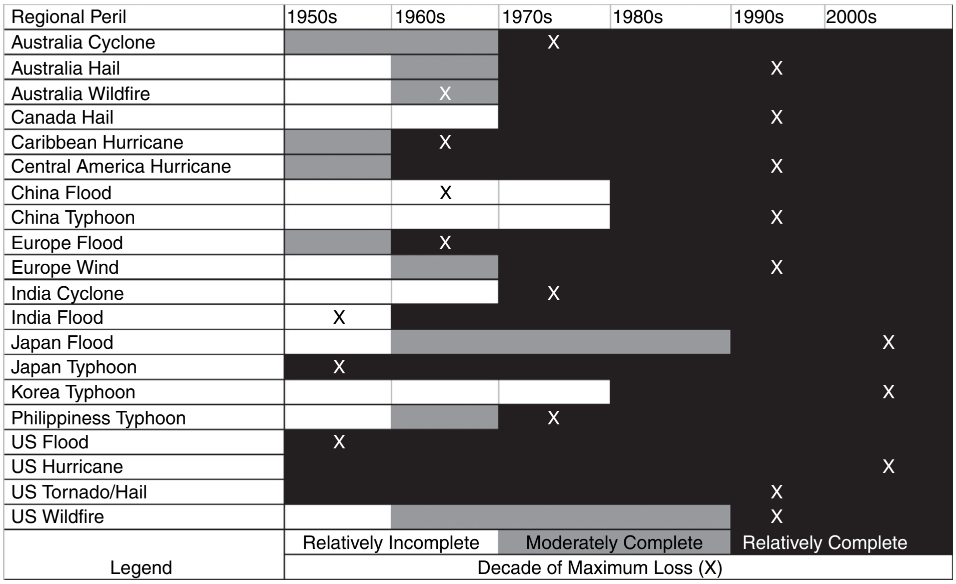

Figure 12.1. Post-1950 data quality for economic losses attributed to weather-related catastrophes by geographic region and catastrophe type.

Data coverage included the largest, best-known catastrophes as well as many smaller and midsize losses in developing regions. Of Swiss Re's list of the 40 costliest insured catastrophe events (Swiss Re, 2006), 36 of these were due to weather-related catastrophes that were included in the study. Data quality varies by region. Datasets from a number of territories are clearly incomplete for the period through the 1950s and 1960s; see Figure 12.1, which presents relative data completeness by decade. For this reason, any assessment of global trends prior to the 1970s has to omit a number of important contributory regions. This figure also illustrates the decade of maximum loss to provide a rough introduction to the pattern of high-loss events over time.

As an example, data for the India cyclone become less reliable for the period before 1965 and likely underreport the extent of losses during this period. Hail loss data for Canada are relatively sparse for the period before 1969. For a small proportion of countries, including China during the later stages of the Cultural Revolution, even for the 1970s the data are incomplete: China typhoon loss data underreport loss estimates prior to 1985; Korea typhoon data are unavailable for the period before 1978. However, despite these challenges, we believe it is possible to develop a global perspective of normalized losses from the 1970s and a more limited "developed world perspective" for the period from 1950.

One of the most challenging countries to which to apply the normalization methodology was Cuba, as a result of issues with converting official losses from Cuban pesos given the discrepancy between the official and black market exchange rates. There were also problems with finding reliable Cuban wealth data (Pielke *et al.*, 2003). Nevertheless, we applied a consistent normalization methodology, recognizing that results may be imprecise. Economic data were taken from the United Nations' (UN) National Accounts Statistics Database and from International Monetary Fund (IMF) statistics. Population data were taken from the UN World Population Prospects: The 2004 Revision Population Database. We used global temperature data from the Climatic Research Unit (CRU) at the University of East Anglia.

12.3 Methodology

We normalized losses to 2005 US dollars (USD) by adjusting for changes in wealth (gross domestic product [GDP] per capita in USD), inflation, and population. This methodology is consistent with that used by Pielke and Landsea (1998) and is given below:

$$\mathrm{NL2005} = \mathrm{L}y * (\mathrm{W2005/W}y) * (\mathrm{I2005})/\mathrm{I}y) * (\mathrm{P2005/P}y), \qquad (12.1)$$

where normalized losses in 2005 USD (NL2005) equal the product of losses in year y and the change ratios in wealth (W), inflation (I), and population (P). Where GDP per capita is expressed in nominal terms, we omit the inflation multiplier.

12.4 Caveats

There are five issues that merit discussion before we proceed to the results.

- The term "economic loss" defies precise definition and is likely to have become broader over time. Today's estimates include direct damages such as physical damage to infrastructure, crops, housing, etc., and indirect damages such as loss of revenue, unemployment, and market destabilization (UN Department of Humanitarian Affairs, 1992). For example, Indonesia's losses from the 2004 tsunami include an estimated US$1.53 billion for initial reduction in economic activity (Overseas Development Institute [ODI], 2005). As there is no systematic way to standardize loss estimates over time, we proceed with the caveat that recent loss estimates may report a more comprehensive and therefore higher economic loss.
- The reporting of economic loss estimates tends to improve with the size of the event (Downton and Pielke, 2005) and over time. Recent losses are almost

everywhere better recorded due to improvements in communications, literacy, news coverage, and insurance penetration. Failing to account for the summation of small to midsize event losses below a certain monetary threshold (e.g., US$1 million) will certainly affect aggregated loss estimates for most countries in earlier decades; however, data on smaller events are both harder to come by and less reliable than those for larger events. The aggregate impact on loss trends for a given country or region is also minimal, which is why the focus here has been on the largest losses.

- The method of normalization employed here assumes a constant vulnerability through time. For wind and hail, vulnerability reflects the susceptibility of buildings to direct damage, while for floods and wildfires it is the degree to which communities have been protected from risk (with flood defenses and firebreaks). The bias of assuming constant vulnerability is strongest where substantial adaptation (mitigation) has occurred, as for normalizing 1950s and 1960s storm surge losses in northern Europe, 1950s and 1960s storm surge and river flood events in Japan, or 1970s wind loss events in Australia. However, for most perils and regions, such as the US hurricane, real reductions in vulnerability have been modest. The impact of adaptation on normalized losses is considered further in Section 12.7. Vulnerability may also change for reasons unrelated to mitigation. Changes in settlement patterns, the development of new structures, and increasing population (e.g., Florida) will also impact a given region's vulnerability.
- The normalization methodology employed uses national statistics to compute the multipliers. Previous US normalizations used state- and county-level data to normalize losses. With the benefit of county-level resolution in the United States, we can see that the population growth rate for certain coastal, hazard-prone regions such as Florida is understated by using the national average. However, we consider the large-scale migration to hazardous coastal areas seen in the United States to be the exception. In the developing countries we surveyed, industrialization has led to migration to urban areas, which generally have lower risk profiles than rural areas. In other countries, there has been a greater balance between urban and coastal migration patterns. For example, high-growth coastal regions such as Queensland, Australia, have a far lower ratio of population growth relative to the national average than Florida.
- For several reasons, US losses exert a strong influence on trend conclusions. Losses are better recorded in the United States than in developing regions, which generates more data points. In addition, the United States has the largest economy and one of the highest GDP per capita levels in the world. There is consequently a higher dollar value of assets at risk in the United States than in most other countries. The US Atlantic basin and Gulf Coast contain a large stretch of coastline that is annually vulnerable to hurricane losses. While the global normalized loss results derived with the methodology above and subsequent trend analysis are technically correct, we emphasize that they are heavily influenced by the large weight of US losses on global totals.

12.5 Normalization results

On a regional basis, the greatest concentration of losses occurs in the United States (36%), followed by China and Europe with 18% and 16% of the total, respectively (Figure 12.2). That regions with higher asset values at-risk should make up the largest shares of the total is not surprising. While normalizing losses to constant dollars allows for a meaningful comparison of losses over time within a region, it may be insufficient to compare losses over time between regions. By normalizing all countries to US GDP per capita, we approximate a homogenous distribution of wealth and control for the large impact of US normalized losses on the global total. If we remove differences that arise purely due to different levels of economic development, the distribution of losses changes noticeably (Figure 12.3). India (52%) and China (38%) account for 90% of the total, and normalized US losses drop from 38% to 3%.

When normalized losses are disaggregated by hazard type, flood is the costliest peril surveyed and accounts for 56% of normalized losses. Normalized tropical cyclone losses also constitute a sizable share (38%). Wind losses account for 4%, and other hazard types account for negligible shares of the total. Figure 12.4 shows the trend in aggregate normalized losses and the trend by hazard type. The volatile pattern of losses in the earlier

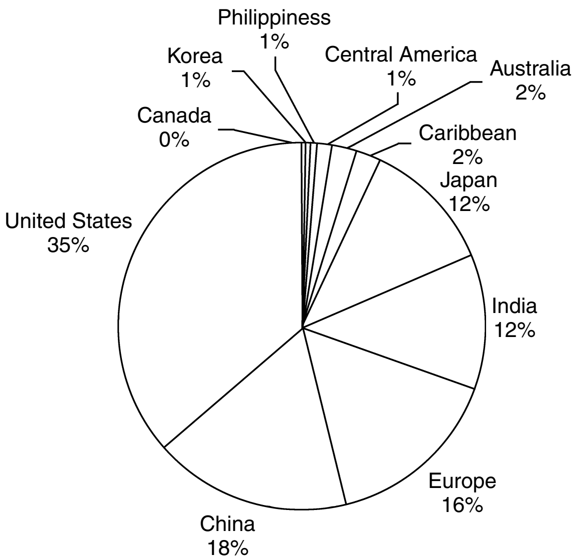

Figure 12.2. Regional distribution of aggregate economic losses from 1950 through 2005, normalized to 2005 USD.

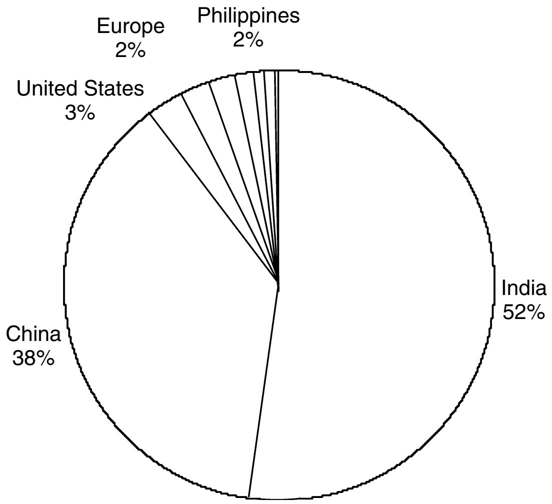

Figure 12.3. Regional distribution of aggregate economic losses from 1950 through 2005, normalized to 2005 USD and adjusted by GDP per capita. Regions not shown constitute less than 2% of the total.

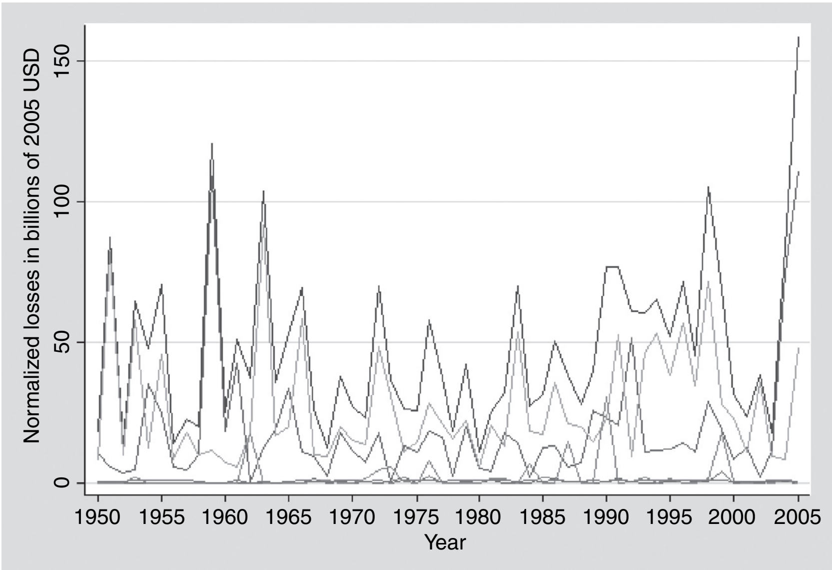

Figure 12.4. Trends in normalized losses for global totals (blue), hurricane (brown), hail (green), flood (yellow), wind (gray), and wildfire (red). See also Plate 23.

decades is principally because the flood data are incomplete for both China and Japan for the period prior to the 1980s. It is notable that even with the incomplete data from the first two decades, the period of the 1970s and 1980s appears to have had lower levels of catastrophe losses than has been seen before or since.

12.6 Trend analysis

To test for a trend in normalized losses over time, we perform a linear regression of normalized economic losses in a given year on the year. The model is given below in Equation (12.2):

$$\mathrm{NL}_y = \alpha + \beta_1 \mathrm{YEAR}_y + \varepsilon_y. \tag{12.2}$$

Normalized losses (NL) in year y are determined by the loss year (YEAR) y, where ε is the error term. If time is a significant determinant of loss level, we would expect the year to be statistically significant. The coefficient sign will indicate the direction of the trend. We fit the regression twice using global normalized loss estimates as well as hazard type and regional subsets, first with data for 1950–2005 and then with data for 1970–2005 (Table 12.A1 in the Appendix). Owing to the large impact of Katrina, 2005 losses are nearly four standard deviations from the mean and exert an upward pull on the overall trend. Overall, US hurricane losses from 2004 and 2005 as well as China flood losses exert a strong influence on the trend. To separate out the impact of these events on the overall results, we ran the regression separately with the respective losses removed (Table 12.A1). The log of normalized losses by year is shown in Figure 12.5.

When it is analyzed over the full survey period (1950–2005), the year is not statistically significant for global normalized losses. However, it is significant with a positive coefficient for normalized losses for specific regions, such as Canada at 10%, Korea at 5%, and China at 1% (in each of which the earlier record is known to be incomplete). The coefficient is negative (but not significant) for Australia, Europe, India, Japan, and the Philippines. Conclusions post-1950 are difficult to make owing to the lack of data. With the information available we do not find evidence of an upward global loss trend.

For the more complete 1970–2005 survey period, the year is significant, with a positive coefficient for (i.e., increase in) global losses at 1% with an r^2 value of 0.20, China at 1% (although again the early part of the record is likely to be incomplete), global tropical cyclones at 5%, and Caribbean losses at 10%. When Katrina losses are removed the global trend is significant at 5%. When US hurricane losses from 2004 and 2005 or China flood losses are removed, the

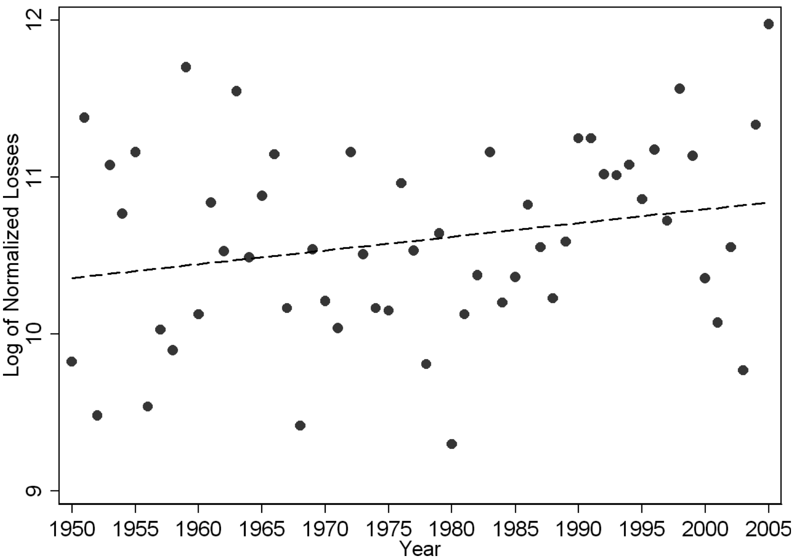

Figure 12.5. Logarithmic plot of global normalized losses from 1950 through 2005.

trend is no longer significant. There is a decreasing trend in normalized losses for the Philippines at 5%, and India at 1% (all located around the eastern Indian Ocean).

12.7 Discussion

12.7.1 Disaster loss trends

Before we consider the implications of these findings, we should first explore potential reasons for trends within the dataset. As was already noted, our methodology does not normalize for changes in the vulnerability of buildings, nor does our regression control for improved mitigation, such as reducing flood risk. However, there are several clear regional examples of declining loss trends since 1950 that merit comment. In Europe and Japan extensive investments in coastal flood defenses, in particular during the 1960s, have been well documented; the actual losses from events such as Typhoon Vera or the 1953 and 1962 North Sea storm surges would consequently be significantly reduced below the normalized values if they recurred today. For flood in Europe (Figure 12.6), the top three loss years all occurred by 1966 and recent flood years have reached less than half the value of the high-loss years in the first 20 years of the record.

While the record of river flood defense improvements in Europe is more mixed than for coastal defenses against storm surges, in Japan the dense

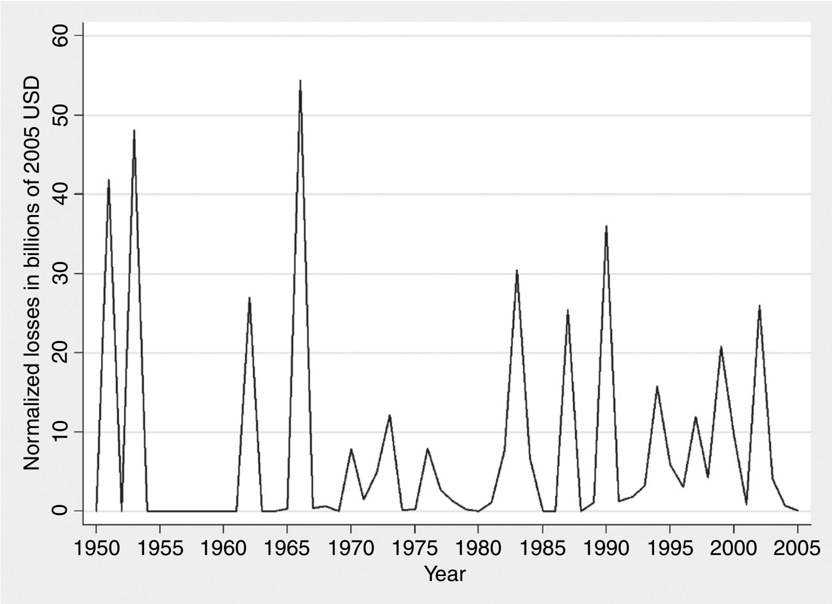

Figure 12.6. Normalized European flood losses from 1950 through 2005.

concentration of urban populations in low-lying areas has required major investments in riverine flood protection schemes throughout the periods of rapid economic growth. The impact of these investments can be seen in the dramatic reduction in the numbers of houses flooded in typhoons from 1950 through 2005 (Figure 12.7). Over the same period, improvements in building quality in Japan and the move away from traditional light wooden houses has also caused significant reductions in the numbers of properties severely damaged or lost in typhoons.

Data from Australia also show a downturn in normalized cyclone damages (Figure 12.8), with the losses from Tropical Cyclone Tracy in 1974 being a record year. However, while there have been significant improvements in building quality since that time, the principal explanation for the trend of declining losses also reflects the absence of any major cyclones hitting highly populated areas.

The reductions in flood losses that can be shown in specific regions are consistent with the overall trend analysis of global flood losses, which shows a decrease in the incidence of high annual totals. However, this has been replaced by more frequent and moderate annual losses, which range between US$20 billion and US$40 billion. The 1990s totals for flood losses are driven by very large flood losses in China, where rapid economic development began 40 years after it did in Japan, and successful flood mitigation schemes have been a feature only since the 1990s.

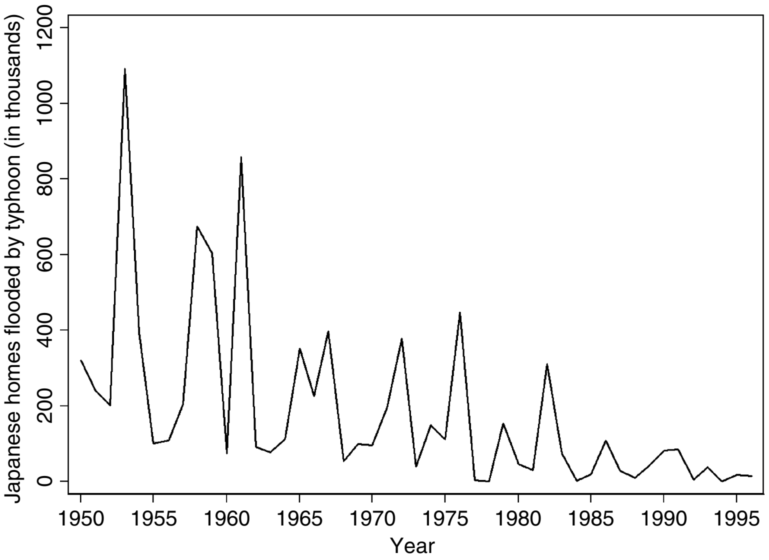

Figure 12.7. Annual estimates of houses flooded due to typhoons in Japan post-1950. Source: RMS estimates.

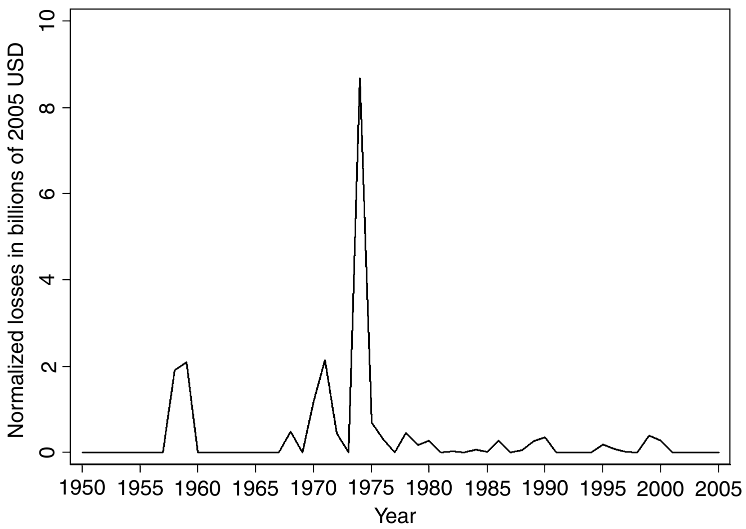

Figure 12.8. Normalized Australian cyclone losses from 1950 through 2005.

The global tropical cyclone loss trend exhibits a lower constant base level compared with floods (Figure 12.4), but it is marked by years with in excess of US$100 billion in normalized losses. A commonality to large flood and hurricane events is the ability of a single event such as Katrina or Vera to dominate losses in a given year and impact trend results over the entire survey period as well. For example, Katrina losses exceed US$100 billion and account for 8% of all normalized tropical cyclone losses, while Typhoon Vera in Japan in 1959 also exceeded US$100 billion of normalized losses. Both these storms generated more than 50% of their economic losses from flooding. The last major program of flood defense improvement in New Orleans was initiated after Hurricane Betsy in 1965. The 2005 flooding of New Orleans could be considered a failure of the 1960s levels of investment in flood mitigation for keeping pace with a rise in hurricane activity. While improved flood mitigation can help explain some part of the reduction of catastrophic flood losses since the 1950s, other causes must be sought in explaining the upward trend in global losses seen since the 1970s.

12.7.2 Climate change

The results of our trend analysis reveal an annual increase in normalized losses of 2%. Isolating the amount of this increase attributable to climate change is difficult, for the various reasons cited earlier. Without fully controlling for other factors that could affect the trend in losses, we can not draw any firm conclusions about the role of climate change in loss trends. In addition, any conclusions about a relationship between global warming and disaster losses are complicated by the sensitivity of statistical results to a few high-loss data points, the short historical loss record, and the limitations of the normalization methodology.

Instead, as a simple exercise we modeled the relationship between the annual global temperature anomaly and annual normalized losses. As a basic test, if there is an underlying link between climate change and normalized losses, we would expect the years with the highest (lowest) temperature variations to also have the highest (lowest) losses.

This relationship modeled is given below:

$$\mathrm{NL}_y = \alpha + \beta_1 \mathrm{TEMP}_y + \varepsilon_y, \tag{12.3}$$

where the total normalized losses in year y (NL_y) are given by the annual global temperature anomaly (TEMP) in year y, which is measured in degrees Celsius relative to the mean temperature from 1960 through 1991. Before we proceed to the results of this exercise, we emphasize that analysis of climatological trends over a span of only 50 years is insufficient to provide definitive conclusions or predictive analysis. The weight of outliers is significant, and one or two data points can exert a strong influence on the trend. Nevertheless, we present the results of this exercise for informative purposes, since the data are

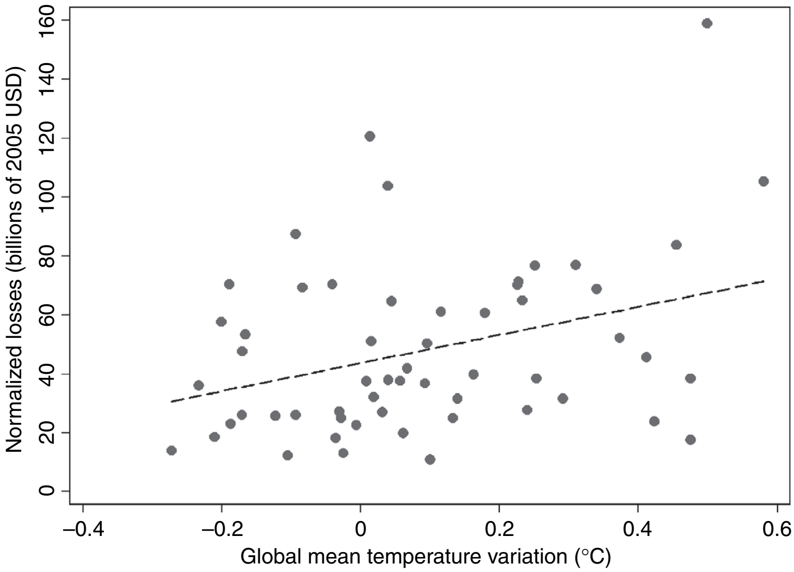

Figure 12.9. Scatter plot of normalized losses by the global temperature anomaly from 1950 through 2005.

largely unavailable for a longer period. Figure 12.9 plots the relationship between temperature variation and normalized losses post-1950.

We caution that our model does not capture the possibility that there are no underlying factors that are common to years of high (low) temperature variation that would cause us to falsely attribute the trend in disaster losses to climatic reasons. Results suggest that the temperature anomaly is highly significant (at 1%) for normalized losses ($r^2 = 0.22$) irrespective of the survey period (Table 12.A2 in the Appendix). Results for Australia, the Philippines, and India are again significant (at the same levels as in the first model) with a negative coefficient. The rise is equivalent to an increase in normalized catastrophe losses of US\$4.8 billion (post-1950) and US\$6.6 billion (post-1970) for each 0.1 °C rise in global temperatures. For details, please refer to Table 12.1A in the Appendix. However, these results are highly dependent upon recent US hurricane losses during 2004 and 2005. When the regression is rerun without these losses, the results are no longer statistically significant (Table 12.2).

12.7.3 Trend sensitivity

To test the impact of various losses on the trends, we performed four simple tests to explore the sensitivity of the results. We repeated the statistical tests in Equations (12.2) and (12.3) in order to isolate the impact of 2004 and 2005 US

Table 12.2. *Summation of trend sensitivity to high-impact events and the dominance of US losses*[a]

	Effect on significance			
	Normalized loss trend		Temperature	
Modification	Post-1950	Post-1970	Post-1950	Post-1970
Complete dataset	not significant	significant at 1%	significant at 1%	significant at 1%
Remove 2004/2005 US hurricane losses	not significant	not significant	not significant	not significant
Remove Katrina losses	not significant	significant at 5%	significant at 10%	significant at 5%
Remove China flood losses	not significant	significant at 10%	not significant	not significant
Renormalized wealth	significant at 5%	not significant	significant at 5%	not significant

[a] Statistical significance disappears for a post-1970 upward trend in normalized losses with the removal of 2004/2005 US hurricane losses and also disappears once we adjust for regional wealth inequalities. The relationship weakens to 5% and 10% with the removal of Katrina or China flood losses, respectively. The statistically significant relationship post-1970 (at 1%) between global temperature and disaster losses disappears once we remove 2004/2005 US hurricane losses or China flood losses, or renormalize wealth. The significance weakens to 5% with the removal of Katrina losses. This result suggests that any conclusion of a relationship between global temperature and normalized disaster losses is highly dependent upon large loss events, particularly in the United States.

hurricane losses, Katrina losses, China flood losses, and regional wealth differences on our results. In the first three instances, we simply reran the regressions with the relevant losses excluded. Since record years for hazard losses in a developing region would not have exerted such a strong pull on trend significance, we renormalized each region's normalized losses by multiplying them by the ratio of US GDP per capita to regional GDP per capita in order to approximate a homogenous distribution of wealth (Tables 12.A3 and 12.A4 in the Appendix). When US hurricane losses from 2004 and 2005 are removed, our results are no longer significant. When losses are renormalized, the results are no longer significant for the post-1970 period. The other modifications weaken our significance findings, but do not eliminate them. Table 12.2 summarizes the impact of these modifications.

12.8 Conclusions

The original purpose of this study was to test the many statements that had been made, and charts that had been plotted, appearing to show a significant increase in global weather-related catastrophe losses over time attributed to a rise in global temperatures and anthropogenic greenhouse gas emissions. We identified several factors that must be considered in interpreting the results: (i) the variance in the definition of economic loss, (ii) improvements in loss reporting over time, (iii) changing vulnerability over time, (iv) national level statistics to adjust loss amounts that affect only a specific national region, and (v) the large weight of US losses in accounting for "global" normalized losses.

Before normalization, the annual rise in losses was about 8%. After normalization, these normalized losses did show a more modest underlying rising trend of 2% per year (from an average of US$36.4 billion in the 1970s to an average of US$64.5 billion from 1996 through 2005: a rise of almost 80%). Therefore, the large portion of the rising loss trend is explained by increases in values and exposure as well as by an increasing comprehensiveness of reporting global losses through time. For specific regions – in particular, India, Australia, and the Philippines – over this same period, there is evidence for a decline in normalized losses.

In sum, we found limited statistical evidence of an upward trend in normalized losses from 1970 through 2005 and insufficient evidence to claim a firm link between global warming and disaster losses. Our findings are highly sensitive to recent US hurricane losses, large China flood losses, and interregional wealth differences. When these factors are accounted for, evidence for an upward trend and the relationship between losses and temperature weakens or disappears entirely.

Finally, it appears that just as hurricane activity and intensity, correlated with a rise in equatorial Atlantic sea surface temperatures (SSTs), have shown the strongest evidence for an increase since the 1970s (Emanuel, 2005), it is hurricanes in wealthy regions that are today the principal driver of the evidence for an upward trend in global catastrophe losses.

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APPENDIX: REGRESSION RESULTS

Table 12.A1. *Ordinary least squares (OLS) regression of normalized weather-related losses on year*

Dependent variable: normalized catastrophe losses.[a]

	Time period					
	1950–2005			1970–2005		
Survey group	Slope	Intercept	r^2	Slope	Intercept	r^2
Global losses	379.26 (241.9)	− 702,039 (478,378)	0.04 —	1251.08*** (423.45)	−2,437,796*** (841,613)	0.20 —
Global losses (2004/2005 US hurricane removed)	19.38 (211.95)	6,155.41 (419,142)	0.000,2 —	395.44 (350.74)	−742,591 (697,107)	0.04 —
Global losses (Katrina removed)	153.69 (211.94)	−258,129 (419,134)	0.01 —	710.54** (340.89)	−1,366,805** (677,520)	0.11 —
Global losses (China flood removed)	99.46 (225.81)	−156,213 (446,556)	0.004 —	698.75* (413.58)	−1,349,145 (821,998)	0.08 —
Peril						
Flood	124.01 (169.37)	−218,293 (334,949)	0.002 —	412.58 (263.38)	−792,552 (523,477)	0.02 —
Hurricane	204.89 (181.7)	−386,844 (359,324)	0.008 —	837.1** (311.51)	−1,645,767 (619,139)	0.16 —
Hail	10.34 (6.35)	−20,101 (12,559)	0.05 —	−1.43 (14.8)	3342 (29,408)	0.003 —
Wildfire	3.45 (2.36)	−6,267 (4,668)	0.04 —	0.41 (4.51)	−217.23 (8,963)	0.000,2 —
Wind	46.38 (45.57)	−89,604 (90,125)	0.02 —	5.47 (101.23)	−8148 (201,194)	0.001 —
Region						
Australia	−3.76 (14.84)	8,333 (29,351)	0.001 —	−50.52 (30.21)	101,391* (60,053)	0.08 —
Canada+	6.87* (4.01)	−13,448* (7,923)	0.05 —	7.72 (9.73)	−15,136 (19,339)	0.02 —
Caribbean	31.09 (19.83)	−60,324 (39,208)	0.04 —	66.44* (35.3)	−130,739* (70,167)	0.09 —
Central America	3.51 (13.59)	−6,286 (26,877)	0.001 —	25.42 (26.57)	−49,953 (52,814)	0.03 —
China +	371.24*** (135.3)	−725,012*** (267,570)	0.12 —	660.15*** (234.16)	−1,300,388*** (465,393)	0.19 —
Europe	−18.6 (109.19)	44,461 (215,936)	0.001 —	128.86 (152.46)	−248,958 (303,021)	0.02 —

Table 12.A1. *(cont.)*

	Time period					
	1950–2005			1970–2005		
Survey group	Slope	Intercept	r^2	Slope	Intercept	r^2
India +	−24.24	53,722	0.01	−285.33***	573,616***	0.25
	(44.5)	(88,001)	—	(84.64)	(168,220)	—
Japan	−174.12	350,072	0.04	101.13	−198,148	0.06
	(120.1)	(237,504)	—	(68.98)	(137,096)	—
Korea +	16.63**	−32,617**	0.08	25.04	−49,366	0.05
	(7.89)	(15,612)	—	(19.21)	(38,175)	—
Philippines	−0.95	2,216	0.0007	−21.89**	43,914**	0.13
	(4.94)	(9,762)	—	(9.92)	(19,718)	—
United States	243.2	−463,054	0.03	652.71	−1,278,026	0.07
	(183.53)	(362,946)	—	(408.88)	(812,658)	—
$n =$	56	—	—	36	—	—

[a] Regression results presented with coefficient on top and standard error in parentheses
+, dataset incomplete and contains several zero values
*significant at 10%
**significant at 5%
***significant at 1%.

Table 12.A2. *OLS regression of global temperature anomaly on normalized losses*
Dependent variable: normalized catastrophe losses.[a]

	Time period					
	1950–2005			1970–2005		
Survey group	Slope	Intercept	r^2	Slope	Intercept	r^2
Global losses	47,805.46***	43,662.99***	0.12	66,032.47***	36,865.44***	0.22
	(17,769.29)	(4,077.56)	—	(21,557.72)	(5,835.75)	—
Global losses (2004/2005 U.S. hurricane removed)	17,287.39	42,930.31***	0.02	26,203.59	38,629.04	0.06
	(16,044.36)	(3,681.74)	—	(17,765.87)	(4,809.29)	—
Global losses (Katrina removed)	28,149.76*	43,280.37***	0.06	40,074.7**	38,195.14***	0.14
	(15,836.4)	(36,34.02)	—	(17,251.5)	(4,670.11)	—
Global losses (China flood removed)	19,131.69	38,764.23***	0.02	34,277.87	33,455.24***	0.07
	(17,109.21)	(3,926.09)	—	(21,291.59)	(5,763.71)	—
Peril						
Flood	22,379.18*	24,926.94***	0.05	28,727.42**	22,287.77***	0.12
	(12,660.64)	(2,905.27)	—	(13,093.69)	(3,544.51)	—
Hurricane	21,560.86	16,392.98***	0.04	35,886.66**	11,514.39**	0.12
	(12,753.8)	(31,56.12)	—	(16,483.66)	(44,62.19)	—
Hail	143.67	340.87***	0.002	−627.42	605.90***	0.02
	(497.29)	(114.11)	—	(751.46)	(203.42)	—
Wildfire	65.18	549.52***	0.002	−117.75	628.60***	0.01
	(183.89)	(42.20)	—	(230.48)	(62.39)	—
Wind	3,875.94	1,764.97**	0.003	1,708.32	2,419.29*	0.003
	(3,480.08)	(798.58)	—	(5,184.73)	(1,403.53)	—
Region						
Australia	−1,500.7	1,025.89***	0.03	−3,511.97**	1,609.05***	0.14
	(1,117.65)	(256.47)	—	(1,495.71)	(404.89)	—
Canada+	780.33**	71.24	0.11	882.35*	48.28	0.09
	(296.28)	(67.99)	—	(480.46)	(130.06)	—
Caribbean	3,620.62**	849.06**	0.10	4,508.85**	497.17	0.17
	(1,470.62)	(337.47)	—	(1,738.78)	(470.70)	—
Central America	952.74	952.74	0.02	2,210.25*	171.08	0.08
	(1,032.29)	(1,032.29)	—	(1,328.3)	(359.58)	—
China+	31,417.38***	6,294.01***	0.15	30,792.82**	6,135.57**	0.16
	(10,188.32)	(2,337.94)	—	(12,252.42)	(3,316.77)	—
Europe	7,723.14	6,995.16***	0.02	12,094.17	4,982.11**	0.07
	(8,289.47)	(1,902.20)	—	(7,625.59)	(2,064.28)	—
India+	−5,531.46	62,72.84	0.05	−13,748.17***	8,987.72***	0.22
	(3,329.68)	(764.07)	—	(4,426.33)	(1,198.22)	—

Table 12.A2. *(cont.)*

	Time period					
	1950–2005			1970–2005		
Survey group	Slope	Intercept	r^2	Slope	Intercept	r^2
Japan	−6,053.15	6,294.55***	0.008	2,861.27	2,341.79**	0.02
	(9,328.73)	(2,140.69)	—	(3,615.41)	(978.70)	—
Korea+	1,393.26**	135.84	0.09	1,468.48	141.61	0.06
	(598.98)	(137.45)	—	(977.72)	(264.67)	—
Philippines	−298.97	−298.97	0.01	−886.61*	567.21***	0.08
	(375.57)	(375.57)	—	(522.46)	(141.43)	—
United States	17,549.67	16,376.69***	0.03	28,339.80	14,142.37**	0.05
	(14,065.9)	(3,227.74)	—	(21,196.26)	(5,737.91)	—
$n=$	56	—	—	36	—	—

[a] Regression results presented with value on top and standard error in parentheses

+, dataset incomplete and contains several zero values

*significant at 10%

**significant at 5%

***significant at 1%.

Table 12.A3. *OLS regression of wealth-adjusted normalized weather-related losses (in billions USD) on year*

Dependent variable: wealth-adjusted normalized weather-related catastrophe losses.[a]

	Time period					
	1950–2005			1970–2005		
Survey group	Slope	Intercept	r^2	Slope	Intercept	r^2
Global losses	9.22**	−17,567**	0.08	3.67	−6,535	0.01
	(4.30)	(8,507)	—	(7.92)	(15,740)	—
Peril						
Flood	4.88	−9,135	0.03	4.08	−7,550	0.01
	(3.77)	(7,447)	—	(6.36)	(12,638.7)	—
Hurricane	4.11**	−7,976**	0.09	−1.34	2,879	0.003
	(1.75)	(3,462)	—	(4.11)	(8,165)	—
Hail	0.008	−15.70	0.03	−0.000,3	0.92	0.000,1
	(0.006)	(12.27)	—	(0.015)	(28.85)	—
Wildfire	0.005	−9.30	0.01	0.01	−26.08	0.02
	(0.009)	(17.58)	—	(0.01)	(28.73)	—
Wind	0.09	−168.19	0.02	0.01	−15.29	0.000,1
	(0.09)	(169.17)	—	(0.19)	(377.65)	—
Region						
Australia	−4.36	9,648.72	0.001	−58.50	117,394.5*	0.08
	(17.19)	(33,984.61)	—	(34.98)	(69,531.92)	—
Canada+	0.01*	−16.53*	0.05	0.01	−18.6	0.02
	(0.005)	(9.74)	—	(0.01)	(23.77)	—
Caribbean	0.27	−523.54	0.05	0.54*	−1,065.68*	0.09
	(0.16)	(319.33)	—	(0.29)	(571.95)	—
Central America	0.03	−47.88	0.001	0.19	−380.47	0.03
	(0.10)	(204.72)	—	(0.20)	(402.26)	—
China+	10.28**	−20,081**	0.11	19.12***	−37,679	0.18
	(3.97)	(7,842)	—	(6.91)	(13,735)	—
Europe	−0.03	83.45	0.001	0.24	−467.30	0.02
	(0.20)	(405.32)	—	(0.29)	(568.78)	—
India+	−1.47	3,252.23	0.01	−17.27***	34,725.67***	0.25
	(2.69)	(5,327.43)	—	(5.12)	(10,183.7)	—
Japan	−0.20	394.86	0.04	0.11	−223.50	0.06
	(0.14)	(267.89)	—	(0.08)	(154.64)	—
Korea+	44.69**	−87,676**	0.08	67.32	−132,700	0.05
	(21.22)	(41,966)	—	(51.63)	(102,619)	—
Philippines	0.04**	−87.68**	0.08	0.07	−132.70	0.05
	(0.02)	(41.97)	—	(0.05)	(102.62)	—
United States	243.2	−463,054	0.03	652.71	−1,278,026	0.07
	(183.53)	(362,946)	—	(408.88)	(812,658)	—
n =	56	—	—	36	—	—

[a] Regression results presented with coefficient on top and standard error in parentheses

+, dataset incomplete and contains several zero values

*significant at 10%

**significant at 5%

***significant at 1%.

Table 12.A4. *OLS regression of global temperature anomaly on wealth-adjusted normalized weather-related losses (in billions USD).*

Dependent variable: wealth-adjusted normalized weather-related catastrophe losses.[a]

	Time period					
	1950–2005			1970–2005		
Survey group	Slope	Intercept	r^2	Slope	Intercept	r^2
Global losses	704.50**	594.13***	0.08	315.70	711.28***	0.02
	(329.14)	(75.53)	—	(403.93)	(109.34)	—
Peril						
Flood	487.79*	462.41***	0.05	350.23	490.90***	0.03
	(284.90)	(65.38)	—	(322.62)	(87.34)	—
Hurricane	191.57	140.48***	0.03	− 75.94	234.91***	0.004
	(138.17)	(31.71)	—	(210.66)	(57.03)	—
Hail	0.008	0.27**	0.001	− 0.62	0.49**	0.02
	(0.48)	(0.11)	—	(0.74)	(0.20)	—
Wildfire	0.57	0.41	0.01	0.94	0.27	0.05
	(0.68)	(0.16)	—	(0.73)	(0.20)	—
Wind	7.28	3.31**	0.02	3.21	4.54*	0.003
	(6.53)	(1.50)	—	(9.73)	(2.63)	—
Region						
Australia	− 1.74	1.19***	0.03	− 4.07**	1.86***	0.14
	(1.29)	(0.30)	—	(1.73)	(0.47)	—
Canada+	0.96**	0.09	0.11	1.08*	0.06	0.09
	(0.36)	(0.08)	—	(0.59)	(0.16)	—
Caribbean	30.20**	6.70**	0.11	36.75**	4.05	0.14
	(11.98)	(2.75)	—	(14.17)	(3.84)	—
Central America	7.26	4.28**	0.02	16.83	1.30	0.08
	(7.86)	(1.80)	—	(10.12)	(2.74)	—
China+	969.97***	164.79**	0.17	1,035.22***	133.0	0.20
	(293.41)	(67.33)	—	(349.92)	(94.73)	—
Europe	14.50	13.13***	0.02	22.70	9.35**	0.07
	(15.56)	(3.57)	—	(14.31)	(3.87)	—
India+	− 334.86	379.75***	0.05	− 832.29***	544.10***	0.22
	(201.57)	(46.26)	—	(267.96)	(72.54)	—
Japan	—	—	—	—	—	—
Korea+	3,745.21**	365.16	0.09	3,947.37	380.66	0.06
	(1,610.10)	(369.47)	—	(2,628.19)	(711.46)	—
Philippines	3.75**	0.37	0.09	3.95	0.38	0.06
	(1.61)	(0.37)	—	(2.63)	(0.71)	—
United States	17.55	16,376.69***	0.03	28,339.80	14,142.37**	0.05
	(14.07)	(3,227.74)	—	(21,196.26)	(5,737.91)	—
$n=$	56	—	—	36	—	—

[a] Regression results presented with value on top and standard error in parentheses

+, dataset incomplete and contains several zero values

*significant at 10%

**significant at 5%

***significant at 1%.