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Trends in Normalized Weather-Related Property Losses in the United States: 1960 to 2018

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Executive Summary

The Spatial Hazards Events and Losses Database for the United States (SHELDUS) provides county-level data for direct economic losses due to natural hazards from 1960 to the present.[1] The data covers property and crop losses, as well as injuries and fatalities. Losses are categorized by hazard: hurricane, tropical storm, flood, tornado, hail, earthquake, etc.[2] This analysis focuses on weather-related SHELDUS property losses, which, for the remainder of the paper, will be referred to simply as "losses".[3]

Losses exhibit a strong upward time-trend in inflation-adjusted dollars. Using data from 1960 through 2018, a straight line fitted to annual inflated-adjusted losses has an upward slope of about $530 million per year, and an exponential curve fitted to the same data has an annual geometric rate of increase of 4.0%.

These results indicate that property losses are trending upwards at a rate much greater than inflation. What is driving this upward trend? Could the trend be explained by increases in "exposure", defined as the total stock of property exposed to weather risks? Or are other factors at play, such as an increase in the frequency or severity of extreme weather events?

This analysis concludes that historical exposure increases are indeed large enough to explain the upward trend in inflation-adjusted losses. Shifts in weather patterns may also have played a role, but detecting a weather-related loss trend is challenging (for reasons described subsequently), and lies beyond the scope of this analysis. To address the challenge of detecting a weather-related loss trend, the paper offers several suggestions for future research.

Using county-level census data for the number of residential housing units and state-level data for the median market value of a residence, estimates of exposure were calculated at the county-level.[4] These county-level estimates, in turn, were used to adjust or "normalize" property losses to reflect exposure growth between the year of each loss and 2018. Assuming that various assumptions hold (to be discussed subsequently), a normalized loss can be interpreted as the loss that would have occurred if a past weather event had encountered 2018 levels of exposure.

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[1] A "direct" weather-related loss is one that is incurred immediately as a result of weather event. In contrast, an "indirect" loss emerges with some delay, in the aftermath of a weather event. For example, if the roof of a seaside rental home is destroyed by a hurricane, the damage to the roof would be consider a direct loss, while the loss of rental income in subsequent weeks and months would typically be considered an indirect loss.

[2] The SHELDUS data covers the following 18 natural hazards: avalanche, coastal, drought, earthquake, flooding, fog, hail, heat, hurricane/tropical storm, landslide, lightning, severe storm/thunderstorm, tornado, tsunami/seiche, volcano, wildfire, wind and winter weather. All of these hazards were included in this analysis with the exception of earthquake, tsunami/seiche and volcano. These three hazards are geological hazards, while the focus of this report is weather-related hazards.

[3] This analysis includes only those losses that occurred in the 50 U.S. states. Losses in U.S. territories (such as Guam and Puerto Rico) are excluded.

[4] While county-level data would be preferable for the market value of residences, it is challenging to obtain such data across the lengthy period of this analysis. In contrast, state-level data is readily available.

Normalized losses were aggregated into national and sub-national annual time series and, using linear regression, trend lines were estimated. Key findings of this analysis are as follows:

- For the period from 1960 to 2018, across the United States (U.S.) as a whole and across all weather hazards, the estimated annual rate of increase of normalized losses is 1.2%, with a 95% confidence interval ranging from 0.0% to 2.4%. Considered alone, this result suggests that normalized losses have trended upwards, implying that the growth of losses has outpaced the growth of exposure. However, these results are sensitive to a small number of catastrophic hurricanes.
- If losses for Hurricanes Katrina (2005), Sandy (2012) and Harvey (2017) are excluded from the analysis, the estimated trend (i.e. rate of annual increase) in normalized losses drops dramatically, from 1.2% to 0.5%, and the 95% confidence interval runs from negative 0.6% to positive 1.6%.[5]
- If hurricane losses are entirely excluded from the analysis, or if the Gulf Coast[6] is excluded, the estimated trend in normalized losses falls to a level close to 0%, with a wide confidence interval on either side of this best estimate.
- If hurricane losses are considered by themselves, the estimated annual rate of increase of normalized losses is 0.9%, and the 95% confidence interval runs from negative 3.5% to positive 5.4%.[7] The confidence interval is quite wide because a time series composed solely of hurricane losses exhibits high year-to-year volatility, making it difficult to detect a "signal" (i.e. a trend) amidst the noise.
- Overall, the results of the analysis do not provide convincing evidence of a trend in normalized losses. Indeed, many researchers who have analyzed normalized weather-related loss data for the United States, and for other countries as well, have arrived at a similar conclusion (see section A8 of the appendix).
- The lack a statistically significant trend is not, by itself, proof that the underlying level of risk has remained unchanged across time. Because weather-related loss data is "noisy", exhibiting high year-to-year volatility, many decades of data may be required to validate a shift in risk, as illustrated in section A7 of the appendix.
- The fact that a small number of catastrophic hurricanes events is responsible for a large portion of total historical property losses (as summarized in section A3 of the appendix) increases the challenge of detecting a trend. Hundreds of years of data may be required to statistically validate a shift in the risk associated with major hurricanes (refer to section A7 of the appendix).
- The lack of a convincing trend in normalized losses implies that exposure growth -- which has greatly outpaced inflation – could plausibly explain the growth in inflation-adjusted property losses across the period from 1960 to 2018. Changes in climate patterns may also have had some influence on historical losses, but this analysis is not designed to reliably estimate its impact.

[5] The National Weather Service determined that, just prior to Sandy's landfall in New Jersey, the storm's characteristics had changed such that it was no longer officially considered a hurricane (https://www.climatecentral.org/news/nws-confirms-sandy-was-not-a-hurricane-at-landfall-15589). For this reason, Sandy is sometimes referred to as a "superstorm". For convenience, this report refers to Sandy as a hurricane.
[6] For this analysis, "Gulf Coast" is defined as the following states that have a coastline along the Gulf of Mexico: Alabama, Florida, Louisiana, Mississippi and Texas. According to SHELDUS data, these states accounted for about 80% of hurricane-related property losses in the U.S across the period from 1960 to 2018.
[7] There is a body of research that suggests that, looking backwards on historical data, there is no long run trend in Atlantic hurricane frequency or severity. This research is a useful backdrop against which to consider the findings presented in this paper. A good summary of hurricane data is provided in the following article*:* https://www.forbes.com/sites/rogerpielke/2019/11/15/no-hurricanes-are-not-bigger-stronger-and-more-dangerous/#36e692054d9e

Methodology

There are numerous factors that could potentially contribute to the upward trend in inflation-adjusted losses:

1. Increases in "exposure" (defined as the stock of residential and commercial property), particularly in high-risk areas such as the Gulf Coast.

2. An increase in the total land area that is either urban or suburban, thus increasing the probability that a weather event will hit a developed area.

3. An expansion of "hardscape", pavement and impervious surfaces that decreases an area's capacity to absorb precipitation, thereby increasing the risk of flooding.

4. An increase across time in the completeness of the SHELDUS property loss data.

5. Increases in the frequency and/or severity of extreme weather occurring as a result of anthropogenic climate change.[8]

6. Temporary multi-decade increases in the frequency and/or severity of extreme weather occurring as a result of cyclical nonanthropogenic climate change. For example, the Atlantic Multidecadal Oscillation has a periodicity of between 60 and 80 years, causing gradual shifts in sea surface temperature that correlate with changes in hurricane activity.[9]

7. A temporary uptick in the number of catastrophic weather events -- such as major hurricanes that strike densely populated areas -- that could occur even in the absence of climate change, due to random weather fluctuations.

In addition to factors that could have an upward effect on losses, there are also factors that could have a downward effect, such as changes in building codes to increase the capacity of manmade structures to withstand extreme weather, improvements in cities' flood mitigation infrastructure, and a more efficient response capacity to limit damages, all of which increase resilience.

The relative contribution of each of the various factors listed above to the upward trend in inflation-adjusted property losses is difficult to determine, but the dominant factor appears to be the increase in exposure. Over the period of this analysis (1960 to 2018), the number and value of residential and commercial properties increased dramatically in the United States. This increase, in turn, has exposed more property to the risk of weather damage. According to census data, between 1960 and 2018 the total population increased by 82%, the number of residential housing units increased by 137%, the average market value of a home increased by about 1900%, and the total estimated value of residential housing increased by 4600%.[10] From 1960 to 2018 across the U.S. as a whole, the estimated market value of the stock of residential housing outpaced inflation by an average of 3% a year.

Using county-level census data for the number of residential housing units and state-level data for the median value of a residence, this study adjusts property losses to reflect exposure growth between the year of each loss and 2018. The result is a set of "normalized" or "exposure-normalized" losses in 2018 dollars.[11]

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[8] "Anthropogenic" climate change refers to changes in climate that are caused by human activity, while "nonanthropogenic" refers to changes in climate that are independent of human activity.
[9] Refer to appendix A6 for more information on the Atlantic Multidecadal Oscillation.
[10] A summary of the census data used in this analysis is presented in section A4 of the appendix.
[11] Normalized Loss = Loss Occurring in Year X * (Exposure in 2018 / Exposure in Year X). This calculation is performed separately by county.

After normalizing the data, trends were estimated by running linear regressions on time series of aggregate annual normalized losses, with "year" as the independent variable and annual normalized loss as the dependent variable. The data was analyzed both as a whole – that is, for the entire United States and for all weather hazards merged together – and using various data subsets (for example, losses with hurricanes excluded). Both linear and exponential trend lines were fitted to each data subset, and a 95% confidence interval was developed for the slope of each trend line.

An upward slope in the trend line fitted to exposure-normalized losses could, in theory, suggest that weather-related risks to property have increased across time. But such an interpretation hinges on six key assumptions:

1. The rate of completeness of the SHELDUS loss data is constant across time. That is, in each year from 1960 to 2018, the data captures a constant share of total direct economic losses.
2. The ability of manmade structures to withstand extreme weather events has remained constant across time.
3. The spatial distribution of property has remained unchanged across time. In other words, the percentage of total land area that is either suburban or urban is constant across time.
4. The ratio of the market value of each property's underlying land to its total market value has remained constant across time.[12]
5. The ratio of the value of each property's contents (furniture, electronics, clothing, etc.) to its total market value has remained constant across time.
6. There is enough data to separate the "noise" associated with random fluctuations in weather from the "signal" associated with a shift in underlying weather distributions.

Violation of any of these assumptions is not only possible, but likely. However, these assumptions were necessary to facilitate the analysis. They represent a limitation that complicates our ability to interpret trends in normalized losses. Despite this limitation, it is worthwhile to evaluate trends in exposure-normalized losses because the approach provides an additional lens – albeit, an imperfect one -- through which to view the historical loss data.

A more complex analysis could potentially improve the loss normalization "lens". For example, the increase in property values across the period from 1960 to 2018 could, perhaps, be disaggregated into a component that captures the appreciation in the value of land and a component that captures the appreciation in the value of manmade structures. The loss normalization process could then be modified to exclude the effects of land appreciation.

Normalization could be further refined by adjusting losses not only to account for the increase in the value of buildings and manmade structures, but also the change in value of their contents (furniture, clothes, TV sets, computers, jewelry, etc.). Devising such an adjustment could be a challenge, but even a rough estimate (or a range of estimates) could be helpful.

[12] The market value of any property is the sum of the value of its underlying land and the value of the structures built on that land. In general, it is the structures – and not that land – that are vulnerable to extreme weather. These two components of property – land and structures – do not necessarily appreciate at the same rate. Yet our exposure-adjustment process implicitly makes this simplifying assumption. This assumption could lead either to an overestimate or an underestimate of the growth of exposure across time.

Additional possible improvements to the normalization process include an adjustment for changes in the resilience of exposed assets (i.e. property), as well as an adjustment to account for the ever-increasing percentage of land that is either suburban or urban.

However, the goal of this paper is not to arrive at a precise set of answers but rather to produce rough results that can serve as food-for-thought for further research. Therefore, for this analysis, it was sufficient simply to adjust losses to reflect the increase in the market value of exposure.

Results

As described previously, county-level losses were normalized using county-level estimates for exposure changes between the year of each loss and 2018. The normalized losses were then aggregated into an annual time series, and, using linear regression, both linear and geometric trend lines were fitted to the data.[13] For each model, a 95% confidence interval was calculated for the slope term. Key results for the geometric model appear in Table 1, and results for the linear model appear in section A1 of the appendix.[14]

Table 1

95% CONFIDENCE INTERVALS FOR THE SLOPE OF A GEOMETRIC LINE FITTED TO NORMALIZED LOSSES

Data Subset	Estimated Trend			Cumulative Impact of Trend from 1960 to 2018			R-Square	Percent of Total Losses
	Low	Center	High	Low	Center	High		
1. Entire Dataset	0.0%	1.2%	2.4%	−0.6%	44.6%	119.1%	6.4%	100%
2. Exclude 3 Costly Hurricanes	−0.6%	0.5%	1.6%	−15.8%	15.4%	63.6%	1.4%	81%
3. Exclude All Hurricanes	−0.8%	0.2%	1.1%	−19.6%	4.6%	39.5%	0.2%	53%
4. All Hazards, but Exclude Gulf Coast	−1.0%	0.0%	1.1%	−25.1%	0.3%	38.7%	0.0%	52%
5. Only Hurricane Losses	−3.6%	0.9%	5.4%	−58.3%	32.9%	633.7%	0.3%	47%

Notes: (a) the 3 hurricanes excluded from row 2 are Katrina (2005), Sandy (2012) and Harvey (2017); (b) the final column on the right shows the percent of total normalized SHELDUS property losses included in the data subset.

When all hazards are considered together (row 1 of Table 1), the data exhibits an upward trend, but the trend diminishes and ceases to be statistically significant if Hurricanes Katrina (2005), Sandy (2012) and Harvey (2017) are excluded (row 2). If all hurricane losses are excluded (row 3) the resulting time series is effectively trendless.[15] Similarly, excluding the Gulf Coast – which accounts for nearly 85% of total hurricane-related property losses in the SHELDUS database – results in a trendless time series (row 4). Lastly, if hurricane losses are considered in isolation (row 5), the resulting confidence interval is so wide (running from negative 3.6% to positive 5.4%) that the best estimate is of little statistical value. The wide confidence interval arises because a time series composed solely of hurricane losses exhibits very high year-to-year volatility, making it difficult to identify a trend.

[13] The geometric model is as follows: log loss (year) = intercept + slope * year, where "year" is measured relative to 1960.

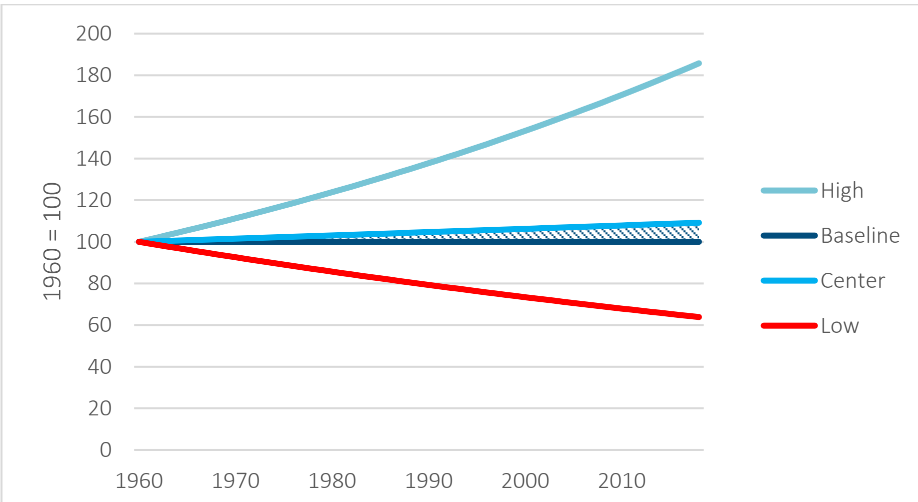
[14] Arguably, the geometric model provides a better conceptual fit to the data because it implies a uniform percent increase in expected normalized losses across time. This seems more plausible than a linear model which implies a gradually decreasing percent growth across time, where growth is measured by comparing the expected loss in year "x" against the expected loss in year "x-1".

[15] In SHELDUS, some losses caused by hurricanes are not categorized as such. For example, because Hurricane Sandy (2012) declined in strength to a tropical storm just prior to making landfall, the associated losses are primarily classified as flood losses. Similarly, about half of the total losses related to Hurricane Harvey (2017) fall into a SHELDUS category other than "hurricane". For the analysis presented in this paper, "hurricane loss" is defined as any loss that appears to be the result of a hurricane, even if, at the time and location of the loss, the storm had declined in intensity such that it was no longer classified as a hurricane.

To better understand Table 1, consider the third row which shows results using data for the entire United States, but excluding all hurricanes. These results are depicted in Figure 1. The best estimate[16] for the trend is positive 0.2% which can be interpreted as the annual rate of growth in expected[17] exposure-normalized property losses. However, there is substantial uncertainty associated with the estimated trend. While the best estimate is 0.2%, the 95% confidence interval runs from negative 0.8% to positive 1.1%.[18] Also, r-squared is merely 0.2%, providing another indication that the level of noise is high relative to the signal, where "noise" is the fluctuation in annual losses that would occur even in the absence of an upward (or downward) trend, and "signal" is the underlying trend. A trendless time series has an r-squared of zero (or close to zero), while a time series with each value falling precisely on the trend line has an r-squared of 100%.

Figure 1

ESTIMATED GEOMETRIC TREND LINES FOR NORMALIZED NON-HURRICANE LOSSES



The "baseline" assumes that expected normalized losses remain constant across time. "Center" is the best estimate trend line fitted to normalized non-hurricane losses, while "low" and "high" correspond to the lower and upper ends of the 95% confidence interval, respectively. The shaded region between "baseline" and "center" represents the best estimate for the cumulative upward effect of the trend across the entire period from 1960 to 2018.

The right side of Table 1 shows the cumulative effect of the estimated trend across the period from 1960 to 2018. Excluding hurricane losses, the best estimate for the cumulative effect is 4.6%; that is, relative to a baseline scenario in which expected losses remain constant across time, the upward trend of 0.2% per year translates into a 4.6% increase in cumulative expected losses across the entire period of analysis.[19] However, the confidence interval surrounding this estimate is quite wide, running from negative 19.6% to positive 39.5%.

[16] In the context of a linear regression, the "best estimate" is the line that minimizes the sum of the squared residuals, where each residual is the vertical distance between the observed and estimated values.
[17] The total weather-related property loss in each year "x" can be viewed as the result of a random process. The expected value of that process is equal to the probability-weighted average of all possible values of the loss.
[18] Each of the confidence intervals shown in Table 1 is based on the presumption that the regression's residuals are normally distributed. For those regressions which excluded hurricane losses, the residuals do indeed appear to be normally distributed. But for the regressions that include hurricane losses, the residuals do not appear to be normal. This may cast some doubt on both on the best estimate and the confidence interval around that estimate.
[19] In Figure 1, the area of the shaded region is equal to 4.6% of the total area beneath the "baseline" scenario.

Discussion of Results

Total normalized losses exhibit an upward trend (row 1 of Table 1), but the trend hinges on a small number of catastrophic hurricanes. When hurricanes Katrina (2005), Sandy (2012), and Harvey (2017) are excluded from the analysis (row 2), the estimated trend diminishes and ceases to be statistically significant.[20]

While a recent uptick in the number of catastrophic hurricanes could potentially imply an increase in hurricane risk, there are several reasons that such a conclusion would be quite premature:

- The period covered in this analysis is arguably too short to statistically validate a shift in the probability of events as infrequent as major hurricane landfalls in the U.S.[21] Similarly, three recent catastrophic hurricanes are too few events to conclude that hurricane risk has increased.
- Most researchers who have carefully studied Atlantic hurricane data have concluded that the data has no long-term trend.[22]
- The Atlantic Multidecadal Oscillation (AMO) has a periodicity of between 60 and 80 years, causing gradual shifts in sea surface temperature that correlate positively with changes in hurricane activity.[23] The period evaluated in this analysis is shorter than the AMO's full cycle, and coincides with the transition of the AMO from its cold phase to its warm phase (refer to appendix A6). Thus, the AMO may have contributed to the upward loss trend shown in row 1 of Table 1. Note that the analysis presented in this report isn't capable of filtering out cyclical trends (or portions of cyclical trends). Rather, it assumes that any trend is monotonic and persistent across time.

Thus, there are numerous reasons to be skeptical of the upward trend shown in row 1 of Table 1, which was estimated using the total of hurricane losses and non-hurricane losses. In regard to non-hurricane losses, the results in row 3 of Table 1 indicate that the data lacks a statistically significant trend.

The lack of a convincing trend in normalized losses implies that exposure growth -- which has greatly outpaced inflation – could plausibly explain the rapid growth in inflation-adjusted property losses across the period from 1960 to 2018.

While anthropogenic climate change could potentially have had some impact on historical losses, two key limitations of this analysis inhibit the estimation of its effects:

1. The normalization process is incomplete, failing to account for all of the non-weather-related forces that affect losses, such as improvements in building codes and an expansion of suburban and urban land area. As a consequence, the resulting normalized losses do not provide an entirely "pure" and unobstructed view of the effects of weather on actuarial risk.
2. Given the high year-to-year volatility of losses, the period studied is too short to statistically validate small or subtle shifts in risk. This problem is exacerbated by the AMO which has a lengthy cycle that exceeds the total number of years in this analysis.

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[20] Hurricane Sandy had diminished in strength to a tropical storm by the time it made landfall. However, for this analysis, "hurricane losses"' include not only losses from hurricanes, but also losses from tropical storms that were classified as hurricanes at some earlier stage of their existence.
[21] Section A7 of the appendix provides a mathematical explanation of this statement.
[22] For example, the paper "Normalized Hurricane Damage in the Continental United States 1900-2017" (2018), by Collins, Crompton, Klotzbach, Landsea, Musulin, Pielke, and Weinkle, concludes that "over the entire dataset that is no significant trend in normalized losses, CONUS hurricane landfalls or CONUS intense hurricane landfalls". Note that "CONUS" stands for "the continental United States".
[23] An analysis of the correlation of the AMO with Atlantic hurricane activity is presented in "The Recent Increase in Atlantic Hurricane Activity: Causes and Implications" (2001), by Goldenberg, Gray, Landsea and Mestas-Nunez. In addition, the following NOAA web page provides an overview of the relationship between the AMO and hurricane activity: https://www.aoml.noaa.gov/phod/amo_faq.php

Suggestions for Future Research

Analysis of extreme weather events (and associated losses) is inherently more challenging than an analysis of shifts in weather averages, such as increases in the average global temperature. By definition, tails of weather distributions involve low frequency events. The lower the baseline frequency, the greater the number of years of data required to determine if that frequency has changed.[24] Yet it is the tails of weather distributions that are, in general, of greatest interest to actuaries, since they are most likely to be associated with large losses.

It is possible that some catastrophic events—such as powerful hurricanes that strike coastal cities that are vulnerable to storm surge – occur so infrequently that they are not amenable to trend analysis. More specifically, the number of years of data required to detect and statistically validate a trend might be quite substantial, possibly exceeding the number of years in a researcher's database.

For the sake of argument, suppose that the annual probability of a Category 5 hurricane making landfall has historically been 3%, and, as a result of anthropogenic climate change, this probability shifts upward to 6%. This shift would clearly represent a significant increase of risk. Yet to demonstrate with 90% confidence that the risk level has indeed increased would require over 300 years of data (see section A7 of the appendix).

Extreme weather events that occur more frequently—such as heavy rainstorms, heat waves, or cold spells—may potentially be more amenable to trend analysis. However, even in these cases, a subtle shift in weather patterns may be hard to detect (while a large shift would be easier to detect).

Given these constraints, researchers focused on the retrospective impact of climate change on actuarial risk will have to pick their battles carefully. It may make sense to divide extreme weather events into two groups: (1) those that occur at such a low frequency that conclusions about historic trends may not be possible given the data limitations, and (2) extreme events that, while infrequent, are sufficiently numerous that they may be amenable to trend analysis. While weather events in group one should not be ignored, researchers may wish to focus most of their work effort on group two.

In addition, consideration should be given to how best to use normalized loss data to evaluate the effects of climate change. Should normalized losses be used as (1) the primary lens through which to assess the effects of climate change on actuarial risk, as in the analysis presented in this paper, or (2) should losses be used solely to assign a rough cost to different types and intensities of weather events?[25] If approach (2) is employed, then researchers would focus their attention on estimating shifts or trends in the frequency and/or severity of extreme weather events, and, with these estimates in hand, would use a loss function to estimate the actuarial cost of the weather shifts.

Given the challenges of developing a complete loss normalization process that fully neutralizes the effects of non-weather-related forces, the most favorable research path appears to be the second option described above: the estimation of trends in extreme weather events, with loss data used simply as a means to assign an actuarial cost to those trends.

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[24] Consider two types of extreme weather events, "A" and "B". Suppose that event "A" occurs, on average, once every 100 years, while event "B" occurs once every 10 years. Suppose further that, due to climate change, the probability of each weather event increases by 10%, to 1 out of every 91 years for event "A", and 1 out of every 9.1 years for event "B". Statistically, it is more challenging to validate the frequency increase for event "A" than it is for event "B."

[25] "No, Hurricanes Are Not Bigger, Stronger and More", an article that recently appeared in Forbes, eviscerates a hurricane analysis that relied solely upon economic loss data to arrive at the highly questionable conclusion that Atlantic hurricanes have increased in frequency and severity. A lesson can be drawn from this story: it is unwise to rely solely upon loss data to reach conclusions about changes in weather patterns.

Lastly, at the risk of stating the obvious, the focus of this paper has been entirely retrospective, using historical data to estimate past trends leading up to the present. Such an analysis may be useful to an actuary who is tasked with pricing the risk associated with today's climate and weather. But the analysis offers little for an analyst who is concerned with how weather risks may evolve in the decades to come; for example, an asset manager who is tasked with estimating the market value of a seaside hotel that will become increasingly vulnerable to the effects of storm surge as sea levels rise in the future, or an investor who wishes to understand how the profitability of a farming business might be affected by future increases in temperature averages and extremes. In these cases, prospective analysis is essential, using models that project rising greenhouse gas levels forward time, and then use this information to predict changes in the earth's natural systems, including the atmosphere and weather.

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Appendix

A1. REGRESSION RESULTS FOR A TREND LINE FITTED TO ANNUAL NORMALIZED LOSSES

In the tables below, the "estimated trend" refers to the slope of the trend line. The slope is the annual rate of change in expected losses. The low and high estimates are the boundaries of the 95% confidence interval, and the "center" or "best" estimate falls at the midpoint of the interval.

The "cumulative impact" results are derived from the corresponding slopes. For example, if hurricane losses are excluded from the analysis, the best estimate for the slope of the geometric trend line is 0.2%. This translates into a 4.6% increase in cumulative expected losses calculated across the entire period of analysis. The 4.6% cumulative increase is captured in Figure 1 (presented earlier in the paper). Specifically, the area of the shaded region in Figure 1 is equal to 4.6% of the total area beneath the "baseline" scenario.

REGRESSION RESULTS USING A GEOMETRIC TREND LINE

Data Subset	Estimated Trend (annual % increase)			Cumulative Impact of Trend from 1960 to 2018			R-Square	Percent of Total Losses
	Low	Center	High	Low	Center	High		
1. Entire Dataset	0.0%	1.2%	2.4%	−0.6%	44.6%	119.1%	6.4%	100%
2. Exclude 3 Costly Hurricanes	−0.6%	0.5%	1.6%	−15.8%	15.4%	63.6%	1.4%	81%
3. Exclude All Hurricanes	−0.8%	0.2%	1.1%	−19.6%	4.6%	39.5%	0.2%	53%
4. All Hazards, but Exclude Gulf Coast	−1.0%	0.0%	1.1%	−25.1%	0.3%	38.7%	0.0%	52%
5. Only Hurricane Losses	−3.6%	0.9%	5.4%	−58.3%	32.9%	633.7%	0.3%	47%

Notes: (a) the 3 hurricanes excluded from row 2 are Katrina (2005), Sandy (2012) and Harvey (2017); (b) the final column on the right shows the percent of total normalized SHELDUS property losses included in the data subset.

REGRESSION RESULTS USING A LINEAR TREND LINE

Data Subset	Estimated Trend ($millions per year)			Cumulative Impact of Trend from 1960 to 2018 ($billions)			R-Square	Percent of Total Losses
	Low	Center	High	Low	Center	High		
1. Entire Dataset	−1	404	810	NA	691	NA	6.4%	100%
2. Exclude 3 Costly Hurricanes	−149	82	312	NA	140	NA	0.9%	81%
3. Exclude All Hurricanes	−103	6	116	NA	11	NA	0.0%	53%
4. All Hazards, but Exclude Gulf Coast	−93	27	148	NA	47	NA	0.4%	52%
5. Only Hurricane Losses	−14	398	810	NA	680	NA	6.2%	47%

Notes: (a) the 3 hurricanes excluded from row 2 are Katrina (2005), Sandy (2012) and Harvey (2017); (b) the final column on the right shows the percent of total normalized SHELDUS property losses included in the data subset.

A2. PROPERTY LOSSES BY HAZARD

TOTAL SHELDUS PROPERTY LOSSES BY HAZARD, 1960 TO 2018, IN BILLIONS OF 2018 USD

Hazard	Inflation-Adjusted		Exposure-Adjusted	
	$Billions	Percent	$Billions	Percent
Hurricane/Tropical Storm[26]	317	39.3%	517	37.2%
Flooding	211	26.1%	319	23.0%
Tornado	62	7.7%	119	8.6%
Severe Storm/Thunderstorm	37	4.5%	88	6.4%
Wind	35	4.3%	76	5.5%
Hail	42	5.2%	70	5.0%
Landslide	20	2.5%	56	4.0%
Winter Weather	27	3.4%	54	3.9%
Wildfire	43	5.3%	61	4.4%
Coastal	3	0.4%	9	0.7%
Drought	5	0.7%	9	0.7%
Lightning	3	0.4%	8	0.6%
Heat	1	0.1%	1	0.1%
Total	807	100.0%	1388	100.0%
Total Excluding Gulf Coast	380	47.1%	725	52.2%
Gulf Coast Only	427	52.9%	663	47.8%

The totals above exclude losses that occurred in U.S. territories (Puerto Rico, Guam, etc.)

[26] Some hurricane-related losses fall outside of this category. For example, almost all of the losses related to Hurricane Sandy (2012) are categorized as “flood” losses, because Sandy declined in strength to a tropical storm just prior to making landfall. Similarly, about half of the total losses related to Hurricane Harvey (2017) are classified as “flood”. Across the entire dataset, about 37% of losses are categorized as “hurricane”, but analysis suggests that an additional 10% is related to hurricanes. Thus, in total, about 47% of losses are related to hurricanes.

A3. MOST COSTLY PROPERTY LOSS MONTHS

The SHELDUS dataset uses monthly time-steps. Table A3 shows the ten most costly months in the dataset, after adjusting losses for exposure. Each row of the table shows the total monthly loss computed by summing across all U.S. counties, along with the weather event that was responsible for the lion's share of the total loss.

Table A3

THE TEN MOST COSTLY MONTHS FROM 1960 TO 2018

Rank	Year	Month	Most Costly Weather Event that Occurred in this Year and Month	Loss in Billions, CPI-Adjusted to 2018	Loss in Billions, Exposure-Adjusted to 2018	Exposure-Adjusted Loss as % of Total SHELDUS Property Losses	Cumulative Total of Preceding Column
1	2005	8	Hurricane Katrina	95.6	131.4	9.5%	9.5%
2	2017	8	Hurricane Harvey	90.2	94.8	6.8%	16.3%
3	1992	8	Hurricane Andrew	45.7	82.6	5.9%	22.2%
4	2012	10	Hurricane Sandy	27.7	33.2	2.4%	24.6%
5	2004	9	Hurricane Ivan	20.2	29.8	2.1%	26.8%
6	1989	9	Hurricane Hugo	7.2	20.4	1.5%	28.2%
7	1965	4	Tornadoes	5.5	18.7	1.3%	29.6%
8	2005	10	Hurricane Wilma	13.1	18.7	1.3%	30.9%
9	2008	6	Inland Flood	13.2	18.4	1.3%	32.2%
10	2018	11	Wildfires	18.0	18.0	1.3%	33.5%

A4. SUMMARY OF DATA USED FOR EXPOSURE ESTIMATES

Table A4 provides national totals of the county-level census data that was used to estimate county-level exposure. Exposure was defined as the market value of residential housing and was estimated by multiplying the county-level number of residential housing units by state-level estimates for the median market value of a residence. An implicit assumption is that the total market value of commercial property has increased at the same rate as the total market value of residential property. This assumption was necessary because an appropriate commercial property database could not be located.

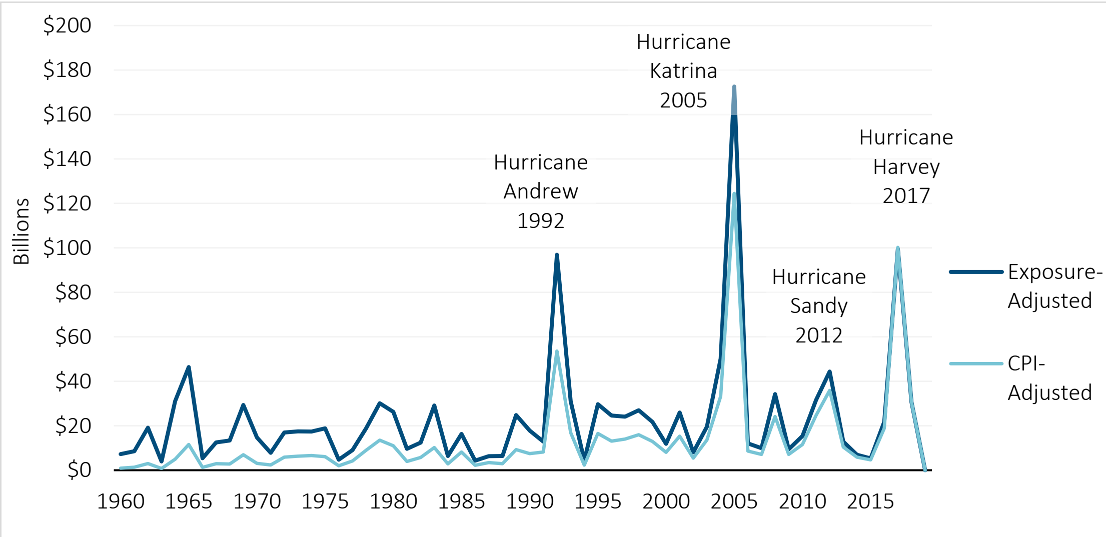
Table A4

SUMMARY OF DATA USED FOR EXPOSURE ESTIMATES

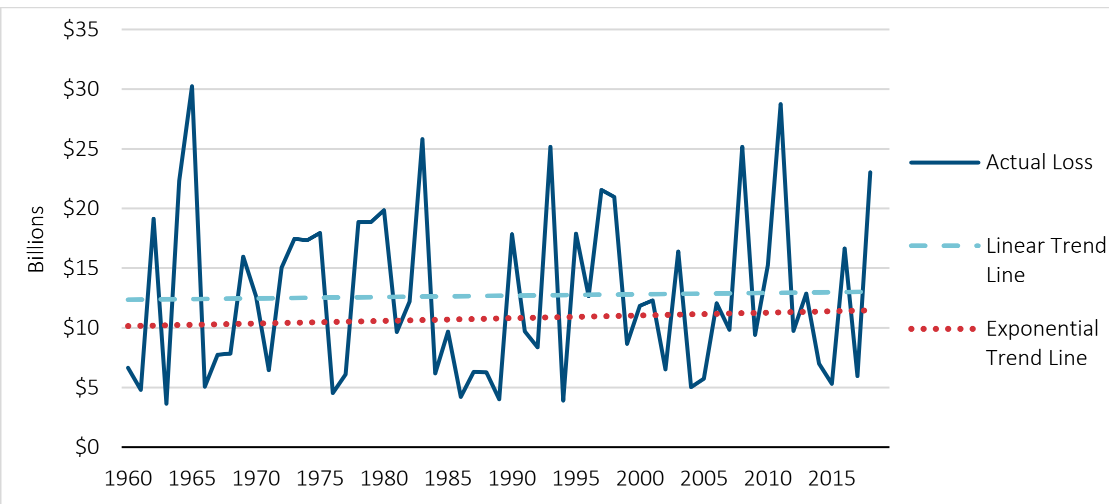
Year	CPI Index	Total Population (Millions)	Number of Residential Housing Units (Millions)	Average Market Value of a Residence (Nominal USD)	Estimated Value of Residential Housing (Billions Nominal USD)
1960	100	179.3	58.3	12,019	701
1970	132	203.2	68.7	17,295	1,188
1980	280	226.5	88.4	49,262	4,355
1990	442	248.7	102.3	94,411	9,655
2000	584	281.4	115.9	126,070	14,612
2010	736	308.7	131.7	167,198	22,021
2018	851	325.9	138.1	236,645	32,669
Rate of Increase	3.76%	1.04%	1.50%	5.27%	6.85%
2018 / 1960	8.51	1.82	2.37	19.7	46.6

A5. TIME SERIES OF ANNUAL LOSSES AND EXPOSURE-ADJUSTED LOSSES FOR THE UNITED STATES

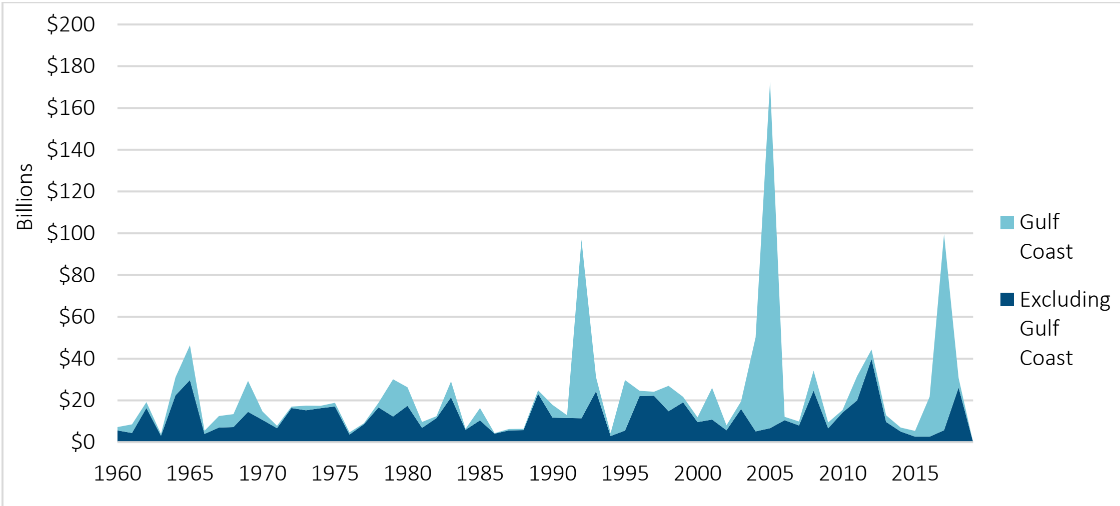
U.S. ANNUAL LOSSES: ALL HAZARDS



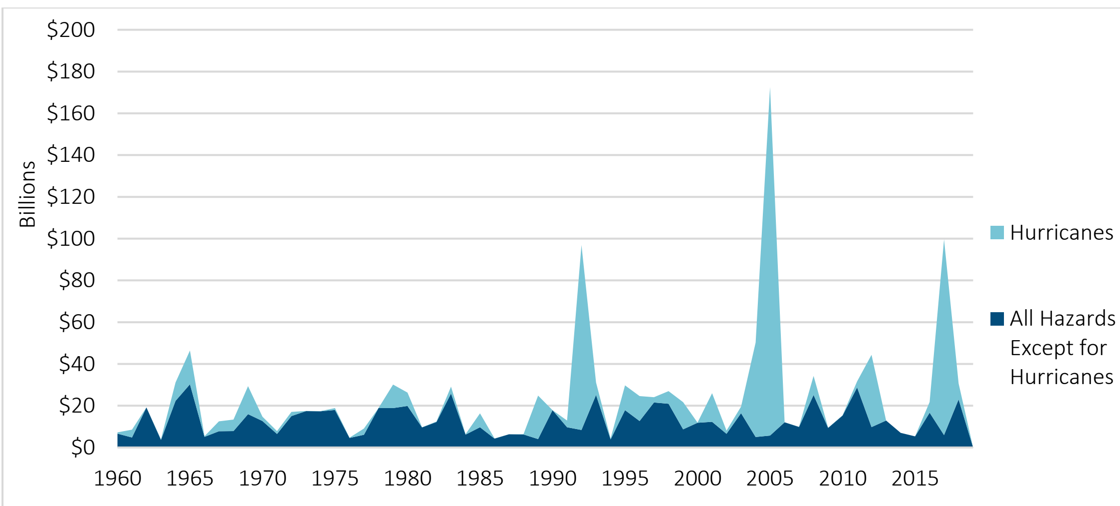
U.S. ANNUAL EXPOSURE-ADJUSTED LOSSES EXCLUDING HURRICANES



U.S ANNUAL EXPOSURE-ADJUSTED LOSSES: GULF COAST VERSUS THE REST OF THE U.S.



ANNUAL EXPOSURE-ADJUSTED LOSSES: HURRICANE VERSUS NON-HURRICANE



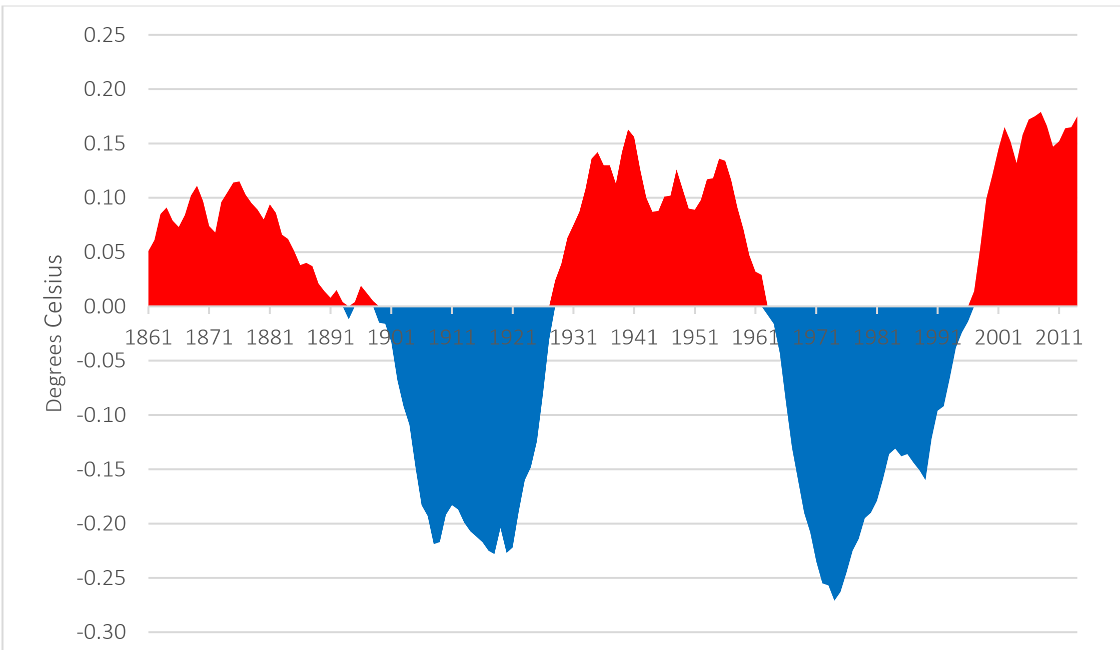
A6. THE ATLANTIC MULTIDECADAL OSCILLATION

The Atlantic Multidecadal Oscillation (AMO) is a long-duration natural cycle that affects sea surface temperature (SST) in the North Atlantic Ocean.[27] Over a period of between 25 to 40 years, SST gradually rises, followed by a period of 25 to 40 years over which SST gradually cools. The cycle then repeats itself.

The AMO is superimposed upon other natural cycles, such as seasonal temperature changes which shift SST upwards and downwards over the course of each year. In addition, anthropogenic warming introduces a monotonic upward trend on SST. The AMO is defined relative to these other sources of SST change.

There is some debate with respect to the amplitude of the AMO, defined as the temperature difference between its peak and trough. The National Oceanic and Atmospheric Administration (NOAA) presents both smoothed and unsmoothed estimates of the AMO time series on its website.[28] A separate time series is presented for each calendar month. Regardless of month, the amplitude of NOAA's smoothed time series is roughly 0.45 Celsius.

NOAA'S SMOOTHED TIME SERIES FOR THE AMO, 1861–2014, FOR THE MONTH OF SEPTEMBER



[27] https://www.aoml.noaa.gov/phod/amo_faq.php
[28] https://www.esrl.noaa.gov/psd/data/timeseries/AMO/

A7. STATISTICAL VALIDATION OF INFREQUENT EVENTS

Suppose that the annual probability of a severe weather event – such as a Category 5 hurricane making landfall – is merely 3%. Suppose further that, as a result of anthropogenic climate change, the probability jumps to 6% (an abrupt increase is unrealistic, but it is a useful fiction for illustrative purposes). How many years of data is required to statistically validate this change of frequency with 90% confidence?

Suppose that "p1" is the annual event probability before climate change, "p2" is the annual event probability after climate change, "n" is the number of years of data in the "before" climate change period (and there are also "n" years of data in the "after" climate change period, such that, in total, we have 2n years of data), x1 is actual number of hurricanes observed in the "before" period, and x2 is the actual number of hurricanes observed in the "after" period. The number of years of data required to demonstrate that p2 has increased relative to p1 is determined as follows:

$$H_0 : p_1 = p_2$$
$$H_1 : p_1 < p_2.$$

$$z = \frac{\hat{p}_2 - \hat{p}_1}{\sqrt{\dfrac{2\,\hat{p}(1-\hat{p})}{n}}},\ \hat{p}_1 = \frac{x_1}{n},\ \hat{p}_2 = \frac{x_2}{n},\ \hat{p} = \frac{x_1 + x_2}{2n}.$$

The null hypothesis is rejected at the 10% significance level if $z > 1.282$.

Now plug in 0.03, 0.06, and 0.045 for the three probability estimates:

$$1.282 = \frac{0.06 - 0.03}{\sqrt{\dfrac{2(0.045)(0.955)}{n}}} = 0.10233\sqrt{n}$$

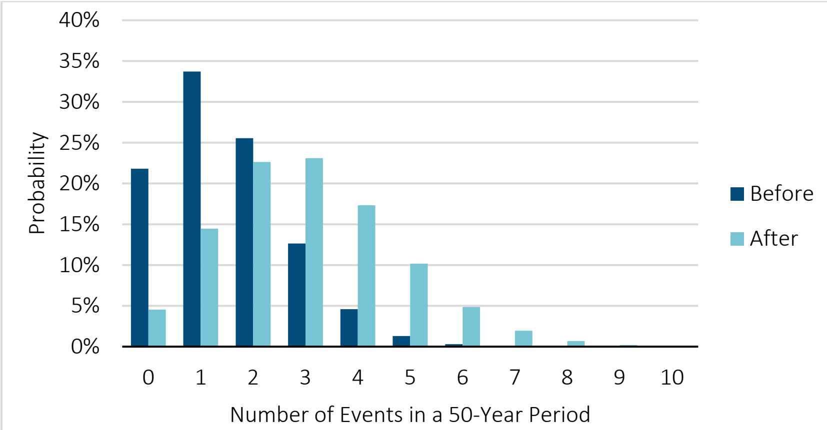
$$n = \left(\frac{1.282}{0.10233}\right)^2 = 157$$

$$2n = 157 * 2 = 314 \text{ (total years of data required)}$$

Thus, in this example, over 300 years of data are required in order to statistically validate that hurricane frequency has increased.

Suppose a researcher attempts to analyze this weather shift with only 100 years of data, consisting of 50 years of data for the "before" weather pattern and 50 years of data for "after". Using the 3% and 6% annual probabilities described above, the number of Category 5 hurricanes occurring in each 50-year period can be described with the following probability distributions:

PROBABILITY DISTRIBUTION FOR NUMBER OF CATASTROPHIC HURRICANES IN A 50-YEAR PERIOD



The "before" period reflects an annual probability of 3%, while the "after" period reflects a 6% probability.

The extensive overlap between the "before" and "after" distributions indicates that 100 years of data is insufficient to statistically validate that the frequency of hurricanes has indeed shifted upwards.

The example above postulates that the annual probability of a catastrophic hurricane increases from 3% to 6% as a result of climate change. This is a relatively large shift. If the shift were smaller – say, from 3% to 4% -- then the number of years of data required to validate the shift would be larger:

YEARS OF DATA REQUIRED TO STATISTICALLY VALIDATE A CHANGE IN EVENT PROBABILITY

Scenario	Hurricane Probability Before Climate Change	Hurricane Probability After Climate Change	Years of Data Required to Statistically Validate that the Probability Has Increased
1	3.0%	6.0%	314
2	3.0%	5.0%	631
3	3.0%	4.0%	2,220
4	3.0%	3.5%	8,269

The required amount of data is even larger if our goal is not only to demonstrate that the event probability has increased, but to estimate the new probability ("p2") within a narrow confidence interval. Suppose that the true value of p2 is 6%, and the statistical goal is to estimate this probability, with 90% confidence, within a range of plus or minus 1%[29]:

1% = 1.645 * [(0.06 * 0.94) / N]^.5

N = [(1.645 / 1%)^2] * 0.06 * 0.94 = 1526 years

This is a sobering result, illustrating the enormous challenge of quantifying the risk posed by catastrophic, low-frequency weather events.

[29] In this example, "plus or minus 1%" is meant in an additive sense rather than multiplicative. Therefore, if the best estimate of p2 were 6%, the 90% confidence interval would run from 5% to 7%.

A8. OTHER RESEARCH USING NORMALIZED WEATHER-RELATED LOSSES

The analytical approach presented in this paper is not a novel one. Other researchers have used this approach or some variant of it. The approach features two basic steps: (1) the normalization of historical loss data in an attempt to remove the influence of the factors unrelated to weather, and (2) an estimation of trends in the normalized time series. A list of some of these research efforts is provided below, along with their key conclusions.

Have Disaster Losses Increased Due to Anthropogenic Climate Change?

Bouwer, 2010

https://www.researchgate.net/publication/249616432_Have_Disaster_Losses_Increased_Due_to_Anthropogenic_Climate_Change

The author examined 22 studies that have "systematically analyzed well-established records from natural hazard losses" in an effort to identify trends that could be associated with climate change. The author summarizes her findings as follows: "the studies show no trends in losses, corrected for changes (increases) in population and capital at risk, that could be attributed to anthropogenic climate change. Therefore, it can be concluded that anthropogenic climate change so far has not had a significant impact on losses from natural disasters. Considerable uncertainties remain in some of these studies, because exposure and vulnerability that influence risk can only be roughly accounted for over time. In particular, the potential effects of past risk-reduction efforts on the loss increase are often ignored, because data that can be used to correct for these effects are not available. More insight into the relative contribution from climate change on disaster losses could potentially be gained from studies that attempt to project future losses. These studies can assess the impact of future climate change, which is projected to be much larger than the change so far observed."

Normalized Hurricane Damages in the United States: 1925-1995

Landsea and Pielke Jr., 1998

https://www.aoml.noaa.gov/hrd/Landsea/USdmg/index.html

The authors use coastal population changes and changes in wealth to normalize historical hurricane loss data. Using the normalized data, the authors conclude that "the trend of increasing damage amounts in recent decades disappears" (in comparison to a trend estimated from non-normalized data).

Normalized Hurricane Damage in the United States: 1900-2005

Collins, Gratz, Landsea, Musulin, Pielke Jr., and Saunders, 2008

https://www.researchgate.net/publication/251194283_Normalized_Hurricane_Damage_in_the_United_States_1900-2005

The authors uses changes in inflation and wealth at the national level and changes in population and housing units at the coastal county level to normalize historical hurricane loss data. The authors conclude that "there is no remaining trend of increasing absolute damage in the data set, which follows the lack of trends in landfall frequency or intensity observed over the twentieth century".

Normalized Hurricane Damage in the Continental United States 1900-2017

Collins, Crompton, Klotzbach, Landsea, Musulin, Pielke Jr, and Weinkle, 2018

https://www.researchgate.net/publication/329192367_normalized_hurricane_damage_in_the_continental_united_states_1900-2017

The authors use changes in inflation, wealth and county-level population to normalize historical hurricane-loss data. The authors conclude that "over the entire dataset that is no significant trend in normalized losses, CONUS hurricane landfalls or CONUS intense hurricane landfalls", where "CONUS" stands for "the continental United States".

Continental U.S. Hurricane Landfall Frequency and Associated Damage: Observations and Future Risks

Bell, Bowen, Klotzbach, and Pielke Jr., 2018

https://journals.ametsoc.org/doi/full/10.1175/BAMS-D-17-0184.1

The authors conclude as follows: "We have investigated trends in CONUS hurricane activity since 1900 and found no significant trends in landfalling hurricanes, major hurricanes, or normalized damage consistent with what has been found in previous studies. CONUS landfalling hurricane activity is, however, influenced by El Niño–Southern Oscillation on the interannual time scale and by the Atlantic multidecadal oscillation on the multidecadal time scale. Despite a lack of trend in observed CONUS landfalling hurricane activity since 1900, large increases in inflation-adjusted hurricane-related damage have been observed, especially since the middle part of the twentieth century. We demonstrate that this increase in damage is strongly due to societal factors, namely, increases in population and wealth along the U.S. Gulf and East Coasts."

Historical Global Tropical Cyclone Landfalls

Maue, Pielke Jr. and Weinkle, 2018

https://www.researchgate.net/publication/258660272_Historical_Global_Tropical_Cyclone_Landfalls

This paper's abstract is as follows: "In recent decades, economic damage from tropical cyclones (TCs) around the world has increased dramatically. Scientific literature published to date finds that the increase in losses can be explained entirely by societal changes (such as increasing wealth, structures, population, etc.) in locations prone to tropical cyclone landfalls, rather than by changes in annual storm frequency or intensity. However, no homogenized dataset of global tropical cyclone landfalls has been created that might serve as a consistency check for such economic normalization studies. Using currently available historical TC best-track records, a global database focused on hurricane-force strength landfalls was constructed. The analysis does not indicate significant long-period global or individual basin trends in the frequency or intensity of landfalling TCs of minor or major hurricane strength. The evidence in this study provides strong support for the conclusion that increasing damage around the world during the past several decades can be explained entirely by increasing wealth in locations prone to TC landfalls, which adds confidence to the fidelity of economic normalization analyses."

An Exploration of Trends in Normalized Weather-Related Catastrophe Losses

Boissonnade, Miller, and Muir-Wood, 2008

https://www.researchgate.net/publication/282754764_an_exploration_of_trends_in_normalized_weather-related_catastrophe_losses

Using weather-related loss data drawn from a large number of developed and developing countries, the authors normalized losses by adjusting for changes in wealth, inflation and population. Using the normalized loss data, the authors searched for trends. One of their main conclusions is as follows: "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."

Normalizing Economic Loss from Natural Disasters: A Global Analysis

Barthel and Neumayer, 2011

https://www.researchgate.net/publication/48910201_normalizing_economic_loss_from_natural_disasters_a_global_analysis

Using normalized loss data computed from a global dataset of natural disaster loss, the authors "find no significant upward trends in normalized disaster damage over the period 1980 to 2009 globally, regionally, for specific disasters or for specific disasters in specific regions. Due to our inability to control for defensive mitigation measures, one cannot infer from our analysis that there have definitely not been more frequent and/or more intensive weather-related natural hazards over the study period already. Moreover, it may still be far too early to detect a trend if human-induced climate change has only just started and will gain momentum over time.

Normalized Insurance Losses from Australian Natural Disasters: 1966–2017

Crompton, McAneney, Mortlock, Musulin, Pielke and Sandercock, 2019
https://www.researchgate.net/publication/249616432_Have_Disaster_Losses_Increased_Due_to_Anthropogenic_Climate_Change
Using data from the Insurance Council of Australia's Disaster List, normalized to reflect changes to the number and cost of residential dwellings, the authors conclude that "there is no trend in normalized losses from weather-related perils; in other words, after we normalise for changes we know to have taken place, no residual signal remains to be explained by changes in the occurrence of extreme weather events, regardless of cause. In sum, the rising cost of natural disasters is being driven by where and how we chose to live and with more people living in vulnerable locations with more to lose, natural disasters remain an important problem irrespective of a warming climate."

Trends in Flood Losses in Europe over the Past 150 Years

Jorkman, Morales-Napoles, Paprotny, and Sebastian, 2018
https://www.nature.com/articles/s41467-018-04253-1.
Using normalized flood losses from 37 European countries, the authors conclude that "after correcting for changes in flood exposure, there has been an increase in annually inundated area and number of persons affected since 1870, contrasted by a substantial decrease in flood fatalities. For more recent decades we also found a considerable decline in financial losses per year. We estimate, however, that there is large underreporting of smaller floods beyond most recent years, and show that underreporting has a substantial impact on observed trends."

A9. TRENDS IN SHELDUS PROPERTY LOSSES REGRESSED ON WEATHER DATA

The analysis presented in this paper relies solely on loss data and exposure data. No weather data was used. Assuming that various assumptions hold (discussed earlier in the paper), a normalized loss can be interpreted as the loss that would have occurred if a past weather event had encountered current levels of exposure. Consequently, trends in normalized losses can, in theory, be directly attributed to trends in weather. In practice, however, it is likely that key assumptions underpinning this theory are violated, such that a trend in normalized losses can arise from sources other than shifts in weather patterns.[30]

An analysis recently released by the American Academy of Actuaries (AAA) uses an innovative approach for estimating the effects of climate change on historical property losses. [31] Not only does the analysis normalize losses in an attempt to neutralize the effects of exposure changes, but weather data is also employed using the following sequence of steps:

1. SHELDUS property loss data for the United States, from 1961 through 2016, is regressed on weather metrics extracted from the Actuaries Climate Index.[32] The dependent variable is the inflation-adjusted loss aggregated across all weather hazards, for a particular year, month and geographic region.
2. The loss estimates produced by the regression are adjusted to account for exposure growth between the year of the loss and 2016. Below, these losses are referred to as "normalized modeled losses", where the term "modeled" indicates that they were produced via a regression.
3. The normalized modeled losses are analyzed to determine if they have increased across time, using the period from 1961 to 1990 as a baseline against which to measure loss increases.

The AAA's analysis concludes that property losses due to climate change amounted to $24 billion (for the period from 1961 to 2016), with a 90% confidence interval running from $2 to $45 billion. The confidence interval is quite compact, equivalent to 0.2% to 3.75% of total exposure-adjusted property losses (which amount to $1.2 trillion across the period from 1961 to 2016). In other words, the analysis arrives at a relatively precise conclusion regarding the effect of climate change on property losses. The analysis indicates that its "measures of uncertainty are somewhat uncertain", but, even so, the narrow confidence interval is striking because it contrasts with the findings of other researchers who, having examined time series of normalized weather-related losses, have generally concluded that various sources of uncertainty make it difficult to arrive at statistically meaningful conclusions about trends in normalized losses.[33]

While the AAA's analysis offers an estimate for the cumulative impact of climate change on property losses across the 1961 to 2016 period, it doesn't translate this impact into an annual trend. However, it is relatively easy to perform this calculation. Table A9.1 presents the annual trends that are consistent with the AAA's cumulative results.

The confidence interval produced by the AAA is much tighter than those produced in this analysis (Table 1 and Table A9.2). A small source of the difference is the fact that the AAA used 90% confidence intervals while the analysis in this paper used 95% confidence intervals. To compare apples with apples, the intervals presented in this paper should be multiplied by 84% (that is, their width should be decreased by 16%).

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[30] For example, a downward trend could be imparted by improvements in building codes, while an upward trend could be imparted by a spatial expansion of exposed assets that isn't explicitly accounted for in the loss normalization process.
[31] The paper is entitled "The Actuaries Climate Risk Index: Preliminary Findings"; https://www.actuary.org/node/13308
[32] The regression uses the unsmoothed and unstandardized monthly time series from the Actuaries Climate Index (ACI) (https://actuariesclimateindex.org/home/). These time series measure various aspects of weather across one-month periods. For example, Rx5day (one of the ACI's metrics) is the maximum rainfall across 5 consecutive days over the course of a month.
[33] Refer to section A8 of the appendix for a list of research papers that focus on normalized weather-related losses.

However, this adjustment doesn't come close to explaining the large difference in the width of the two sets of intervals. The source of the difference must lie elsewhere.[34]

Table A9.1

TRANSLATION OF THE AAA'S ESTIMATED CUMULATIVE IMPACT OF CLIMATE CHANGE INTO AN ANNUAL GEOMETRIC TREND

	Low	Center	High	High–Low
Estimated Cumulative Impact of Climate Change (Billions)	$2	$24	$45	$43
Cumulative Impact as % of Total Exposure-Adjusted Losses	0.17%	2.00%	3.75%	3.58%
Equivalent Annual Geometric Trend [35]	0.006%	0.072%	0.133%	0.127%

Table A9.2

KEY RESULTS OF THE ANALYSIS PRESENTED IN THIS PAPER (REPEATED FROM TABLE 1)

	Low	Center	High	High–Low
Cumulative Impact Percent[36] Using Entire Dataset	-0.6%	44.6%	119.1%	119.7%
Cumulative Impact Percent[36] Excluding Hurricanes	-15.8%	15.4%	63.6%	79.4%
Geometric Trend (1960 to 2018), Using Entire Dataset	0.0%	1.2%	2.4%	2.4%
Geometric Trend (1960 to 2018), Exclude 3 Hurricanes	-0.6%	0.5%	1.6%	2.2%

Perhaps the AAA's more complex methodology -- involving weather data in addition to loss and exposure data -- facilitates tighter confidence intervals. If this is true, then, in theory, the time series of annual normalized modeled losses produced by the AAA's analysis would exhibit relatively low year-to-year volatility.[37] It is worthwhile, therefore, to examine this time series, and to fit a trend to it using linear regression. This approach for analyzing normalized modeled losses produces an estimated annual geometric rate of increase of 0.11% (Table A9.3), which translates into a cumulative impact of 3.1% across the period from 1961 to 2016 (Table A9.4). This is in the ballpark of the AAA's $24 billion estimate which is equivalent to 2% of total exposure-adjusted losses. However, the confidence intervals in Tables A9.3 and A9.4 are much larger than those produced by the AAA. For example, in Table A9.4, the 90% confidence interval for cumulative percent impact runs from negative 12.4% to positive 22.3%, while the AAA's confidence interval runs from positive 0.17% to positive 3.75% (as shown in table A9.1).

[34] An additional consideration is that the AAA's analysis covers the period from 1961 to 2016, while the analysis presented in this paper uses data from 1960 to 2018. However, as a test, the methodology used in this paper was applied to the period from 1961 to 2016, and this had virtually no effect on the resulting confidence intervals.

[35] These estimates assume that the trend runs continuously across the period of analysis, from 1961 to 2016. Alternatively, suppose that climate change has no effect on losses through the year 1990, and that its effects are confined to the period from 1991 to 2016. In this case, the best estimate for the trend would be 0.31%, with a 90% confidence interval running from 0.03% to 0.57%.

[36] Cumulative impact as a percent of total exposure-adjusted losses.

[37] If volatility were high, it would complicate efforts to detect the climate change "signal" amidst the noise associated with random weather fluctuations, leading to a wide confidence interval for the estimated signal.

FIGURE A9.1
NORMALIZED MODELED PROPERTY LOSSES AND BEST ESTIMATE FOR GEOMETRIC TREND LINE

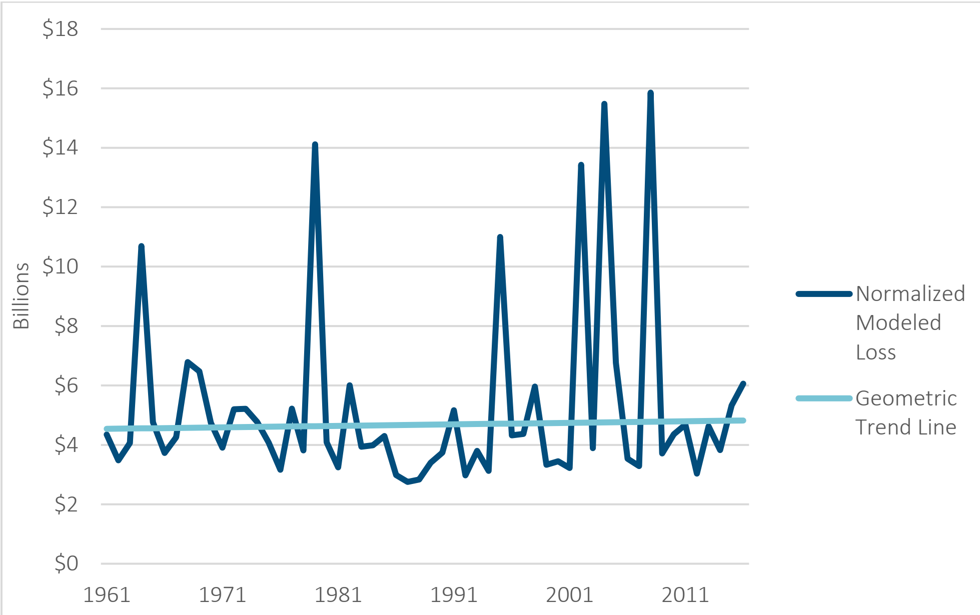

Table A9.3
CONFIDENCE INTERVALS FOR THE SLOPE OF A GEOMETRIC TREND LINE FITTED TO NORMALIZED MODELED LOSSES

Confidence Interval	Low	Center	High	High–Low
90%	−0.49%	0.11%	0.71%	1.20%
95%	−0.61%	0.11%	0.83%	1.43%

Table A9.4
CONFIDENCE INTERVALS FOR THE CUMULATIVE PERCENT IMPACT OF THE TREND IN NORMALIZED MODELED LOSSES

Confidence Interval	Low	Center	High	High–Low
90%	−12.4%	3.1%	22.3%	34.7%
95%	−15.1%	3.1%	26.7%	41.7%

The AAA's results indicate a high confidence that climate change has indeed had an upward impact on property losses; in contrast, the results in Table A9.4 indicate that the trend is not statistically significant.

In addition to the trend uncertainty that is implicit in the year-to-year volatility of the normalized modeled losses, there is an additional layer of uncertainty that arises because the AAA's calculations – like the calculations presented in this paper -- involve an exposure adjustment. As discussed earlier in this paper, there is no "perfect" or "complete" method for implementing exposure adjustments. Such adjustments are rough and may be subject to systematic underestimation or overestimation. For example, if the value of land has appreciated faster than the value of manmade structures, then the exposure adjustments will be too strong because they assume that land and manmade structures have appreciated at the same rate. Also, the exposure adjustments assume that (1) the ability of structures to withstand extreme weather has remained constant across time and (2) the spatial distribution of exposed assets has remained constant across time. If these assumptions do not conform to reality, then the results of the analysis may be tainted by factors unrelated to climate change.

Lastly, although exposure estimates are available for each U.S. county, the AAA applied exposure adjustments at the level of large geographic regions. The AAA's analysis divides the U.S. into seven large regions, and assumes that exposure changes are uniform across all states and counties. This adds another layer of uncertainty because, in fact, exposure has expanded at significantly different rates within each of the seven regions. For example, Florida was grouped into a large region spanning 13 states in the Southeastern U.S. From 1961 through 2016, the number of housing units in Florida increased by about 425%, while the number of units in the entire Southeastern U.S. expanded by only 214%. This is of material importance to the analysis because Florida represents a large share of total SHELDUS property losses (about 15% of inflation-adjusted losses). On an annualized basis, the number of housing units in Southeastern U.S. grew at a rate of 1.4%, while in Florida the rate of growth was 2.7%. This is a large difference, particularly given that the AAA has estimated a narrow confidence interval for the impact of climate change on losses, with a width of merely 0.127% if expressed in the form of an annualized trend (as shown in Table A9.1).

In general, growth of exposure in coastal areas has exceeded growth in inland areas, and coastal areas are, in general, more exposed to extreme weather risks than inland areas. This difference between inland and coastal growth rates cannot be accounted for when using large geographic regions, each of which is composed of a mixture of coastal areas and inland areas.

To achieve a narrow confidence interval for the estimated effects of climate change on losses, it is necessary to eliminate or neutralize most or all of the major factors unrelated to weather that could potentially taint the results. Suppose a study concludes, with 90% confidence, that the annual rate of growth of property losses has been pushed upwards, due to climate change, by between 0.05% and 0.15%, with a best estimate of 0.10%. Suppose further that the study has employed exposure adjustments as part of its calculation sequence. Lastly, for the sake of argument, suppose that the rate of exposure growth was systematically underestimated by 0.1%. This seemingly small error would have a dramatic effect on the study's conclusions, as illustrated in Table A9.5. While the "before correction" results in Table A9.5 indicate that climate change has had a small but statistically significant upward effect on the growth rate of property losses, the "after correction" results do not permit such a conclusion. Rather, the best estimate of the corrected analysis indicates that climate change has had no effect on losses.

Table A9.5
RESULTS OF A HYPOTHETICAL ANALYSIS: ESTIMATED SHIFT, DUE TO CLIMATE CHANGE, IN THE ANNUAL GROWTH RATE OF PROPERTY LOSSES, BEFORE AND AFTER CORRECTION FOR SYSTEMATIC ERROR IN EXPOSURE DATA

	Low	Center	High	High – Low
Before Correction	0.05%	0.10%	0.15%	0.10%
After Correction	−0.05%	0.00%	0.05%	0.10%

The discussion and comments above are an effort to better understand the aspects of the AAA's methodology that lead to a compact confidence interval for the effects of climate change on losses. The AAA's paper sketches out its methodology in broad terms, but without the detail required for a researcher to replicate the approach. So that other researchers can fully understand the mechanics of the AAA's analysis, it would be helpful to have a more detailed description of the calculation of the confidence interval. Also, some additional explanation of the rationale for regressing the loss data on the unstandardized time series of the Actuaries Climate index (ACI) would be useful.[38]

While further clarification of some points would be helpful, the Academy is to be commended for its recognition that loss data, by itself, is insufficient for determining the effect of climate change on actuarial risk. Rather, both loss data and weather data are needed. By using both types of data in its analysis, the Academy has provided valuable food-for-thought for other researchers.

[38] It would be helpful to have a more detailed explanation of why, in the AAA's view, a "modeled" loss provides greater analytical value than the loss itself. The portion of loss variation explained by the regression model is relatively small. In general, the model overestimates relatively small losses and significantly underestimates larger losses. For example, the actual inflation-adjusted loss from Hurricane Katrina (2005) was $92.9 billion according to SHELDUS data, while the modeled loss was only $0.8 billion. Similarly, the actual inflation-adjusted loss for Hurricane Andrew (1992) was $44.4 billion, while the modeled loss was only $64 million. The 10 largest loss observations in the database of 4704 observations account for $241 billion in losses – about 40% of total inflation-adjusted SHELDUS property losses from 1961 to 2016 – while the corresponding set of modeled losses amount to merely $12 billion. It is arguable, therefore, that the regression leads to the loss of valuable information, and that an examination of trends in actual loss data would provide greater insight than an examination of trends in modeled losses. Alternatively, if the AAA's view is that modeled losses represent the portion of actual losses that is due to climate change, this idea needs to be further explained. It is unclear how the regression extracts the effects of climate change given that the unstandardized ACI metrics used in the regression are simply weather metrics (as opposed to climate metrics). The ACI's unstandardized (and unsmoothed) weather metrics jump up and down from month to month, capturing the volatility of weather, as opposed to representing the "signal" due to climate change.

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