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An Economic Analysis of Climate Adaptations to Hurricane Risk in St. Lucia

Chieh Ou-Yang[a], Howard Kunreuther[b] and Erwann Michel-Kerjan[b]
[a]Economics and Finance, City University of Hong Kong, 83 Tat Chee Avenue, Kowloon Tong, Kowloon, Hong Kong.
[b]The Wharton School, University of Pennsylvania, 3730 Walnut Street, Jon M. Huntsman Hall, Philadelphia, PA 19104, U.S.A.

We introduce a catastrophic risk model that captures the cumulative impact of climate change on future expected losses from hurricane risk. The annual growth rates of expected losses due to change in climate patterns (or "climate change factor") are estimated based upon historical storm activities in the Atlantic Basin and catastrophe modelling. The percentiles of the climate change factor are then used to measure expected hurricane losses in the Caribbean Island of St. Lucia. We also undertake benefit-cost analyses on four adaptation measures for homes in St. Lucia and determine when those are cost-effective for different time horizons and discount rates with and without climate change. Adaptation makes an enormous difference and can offset additional losses even with a high climate change factor by making houses much more resilient. Enforcing these protection measures will be critical.
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Introduction

The losses caused by great natural disasters have increased dramatically in recent years, especially after 1990, largely explained by higher population density and increasing development in hazard-prone areas.[1]

Climate change may also amplify weather-related natural disasters by raising the magnitude and/or frequency of these extreme events.[2] Recent studies indicate that increasing concentrations of greenhouse gases are the major cause of warming in the atmosphere and oceans.[3,4] The number, track, rainfall quantity and intensity of

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[1] Changnon (2003); Muir-Wood *et al.* (2006); Miller *et al.* (2008); Cromption and McAneney (2008); Kunreuther and Michel-Kerjan (2011).

[2] Hawker (2007).

[3] Human behaviours, including the burning of fossil fuels, deforestation and other land use changes, contribute to the emission of carbon dioxide and other greenhouse gases, such as methane, which have accumulated in the atmosphere since late 19[th] century. Greenhouse gases trap heat more easily, resulting in higher surface air temperature. IPCC predicts that global average surface temperatures will increase 1.1°C ~ 2.9°C under a low emission scenario and 2.4°C ~ 6.4°C under a high emission scenario. Stern (2006) also suggests that positive feedback mechanisms of climate change, such as releases of methane resulting from melting of permafrost and a reduced uptake of carbon that caused by shrinking Amazon

tropical cyclones might also change with global warming, causing more intense and/or frequent climate disasters, such as storms, floods and droughts. Sea level rise and potentially stronger storms also pose a more intensive threat to the economy, particularly in coastal areas.[5,6]

At the same time, several climate models indicate a possible decrease in hurricane activity in certain regions of the world. Controlling for socio-economic influences, such as increasing population and assets in risk-prone areas, most studies cannot attribute the recent trend of hurricane damages to climate change.[7] But if climate change does impact on the frequency and/or severity of extreme climate events in the future, a crucial feature will lie in its irreversibility.[8]

This paper proposes a simple model that captures this irreversibility element. We use a growth model ($(1+a)^t$ model) to integrate the cumulative effect of a changing climate on expected losses from climate hazards. This effect will of course vary for different geographic regions, hazards and over time. The parameter a can be estimated from observational data and catastrophe modelling of hurricanes and reflects the impact of climate change on physical house damage due to greenhouse gas (GHG) emissions that impacts on global average temperature changes.

The use of a growth model $(1+a)^t$ is consistent with the Dynamic Integrated Climate-Economy model (DICE model).[9] It extends neoclassical economic growth theory by including the natural capital of the climate system as another kind of capital stock with the damages due to climate change proportional to world output and changing with global mean temperature. This property implies that the damages will depend on climate-related factors and will accumulate over time. This assumption is consistent with our growth model where we focus on the damages to individual houses from local climate hazards in a specific region rather than estimating its impact on world output.

In this paper, we focus on hurricane risks in the Atlantic Basin and run a series of simulations to calibrate our model. More specifically, we estimate the parameter a that most closely captures the impact of climate change on expected future hurricane losses using historical storm activities and a hurricane risk model provided by Risk Management Solutions (RMS). We then analyse the impacts of future hurricane risk to residential houses in St. Lucia, an island in the Caribbean.

forest, may amplify greenhouse gas concentrations and lead to global warming that is more severe than anticipated by climate models.

4 Stern (2006); Intergovernmental Panel on Climate Change (IPCC) (2007).

5 Over the next 100 years, higher sea level provides an elevated base for storm surges to build upon and diminishes the rate at which low-lying areas drain, thereby extending coastal inundation from rainstorms. Greater flood damages are also driven by increases in shore erosion, removing protective dunes, beaches, and wetlands and thus leaving previous protected properties closer to the water's edge (U.S. Climate Change Science Program, 2009).

6 Rapley (2006); Stern (2006); Wood *et al.* (2006); IPCC (2007); U.S. Climate Change Science Program (2009).

7 Bouwer and Botzen (2011).

8 Heal and Kristrom (2002).

9 Nordhaus (2008).

We are also interested in possible adaptation measures undertaken by residents to lower their expected loss. In recent years, there has been increasing interest in undertaking adaptation measures that can cost-effectively reduce the potential damage against future natural disasters and maintain insurability, protecting lives and properties.[10,11] For example, houses' roof and windows can be retrofitted or reinforced to withstand hurricanes. However, these measures can have high up-front costs and there is evidence from the literature that many homeowners are unlikely to invest in them because they underestimate the likelihood of future disasters and only consider the expected benefits of these measures over the next few years.[12] It might also be the case that individuals do not know what measures are cost-effective over a given period of time.

This paper also evaluates the relative attractiveness of four alternative adaptation measures through benefit-cost analyses using scenarios based on empirical loss data and estimates of climate change impact by climate scientists. We select St. Lucia as the illustrative example because it is located in the Caribbean's, one of the world's most active hurricane regions. The Caribbean is at risk from hurricanes that are expected to change in intensity (upper or lower) under different climate scenarios. We also have access to catastrophe modelling capacity by RMS. This allows us to quantify the expected benefits of these adaptation measures on specific types of constructions in St. Lucia. Although the results of benefit-cost analyses provide quantitative estimates, they serve more as an illustrative example rather than a quantitative justification for investment today.

This paper is organised as follows: The next section introduces our simple catastrophic risk model with potential cumulative climate change impact. The subsequent section presents the approach to estimate the climate change factor a using historical storm activities in the Atlantic Basin and RMS Caribbean Hurricane Risk Model. In the latter section, we simulate hurricane risk in St. Lucia using our model, the estimates of climate change factor, and loss data with four adaptation measures. Based on the simulations, we show the interplay of climate change and adaptations on hurricane losses for different timescales. In the penultimate section, we conduct benefit-cost analysis on the four adaptation measures to determine which one would be most cost-effective as a function of the time horizon, discount rate and degree of climate change. The final section concludes.

[10] According to IFRC (2001), worldwide investments of US$40bn in disaster preparedness, prevention and adaptation have reduced global economic losses by US$280bn during the 1990s. Kreibich *et al.* (2005) analysed the impact of building precautionary measures for the Elbe flood of Germany in 2002. They found that use of buildings and interior fitting adapted to flooding reduced damage to buildings by 46 and 53 per cent, and damage to contents by 48 and 53 per cent, respectively. Moreover, Kunreuther and Michel-Kerjan (2011) model hurricane damage in Florida, New York, South Carolina and Texas in situations with and without adaptations according to recent building code standards. The results for a 100-year hurricane indicate that adaptation could reduce potential losses by 61 per cent in Florida, 44 per cent in South Carolina, 39 per cent in New York and 34 per cent in Texas. Saving in Florida alone due to adaptation would be US$51bn for a 100-year event and US$83bn for a 500-year event.

[11] IFRC (2001); Kreibich *et al.* (2005).

[12] Kunreuther *et al.* (2013).

Table 1 Definitions of notations

p: Annual probability of a climate disaster	
L: Economic losses from a climate disaster with no climate change impact	
T: Total observed years	
τ: The time before climate change starts to impact economic losses	
a: Annual growth rate of economic losses once climate change impact starts	

A catastrophic risk model with potential climate change impact

Climate change could play a critical role in estimating future catastrophic risk since it will modify the distribution of expected losses upward or downward. We assume that a climate disaster (e.g. a hurricane) could impact St. Lucia with an annual probability p[13] over the next T years. Timing of the climate change state is uncertain and follows a discrete uniform distribution[14] during the T years. That is, climate change will impact economic losses in each year with possibility $1/T$. If climate change starts to impact economic losses in year τ ($1 \leqslant \tau \leqslant T$), the potential catastrophic loss increases gradually with an annual growth rate, a, until year T. The occurrence of a catastrophe and the occurrence of climate change are mutually independent. If there is no climate change effect, the economic loss resulting from a disaster is assumed to be a constant, L. Table 1 defines the notations used in this section.

The annual growth rate, or what we call here the "climate change factor" a, can reflect an external index, such as the average wind speed of all storms and hurricanes occurring in a specific region of the globe in a given year. The higher the average wind speed, the greater the loss caused by a hurricane making landfall in a populated area. If climate change starts to impact economic losses in year τ and a storm hits the area in year $t > \tau$, the expected loss caused by the storm becomes $(1+a)^{t-\tau}L$. The loss is L if $t \leqslant \tau$.

The parameter a can be estimated for a specific geographic region and period of time depending on the available historical climate data. For simplicity, we begin here with a certain value of a to illustrate the cumulative impact of climate change on economic losses. In the next section, we will relax this assumption and quantify a distribution of values for the parameter a for hurricane risks in St. Lucia from historical storm activity in the Atlantic Basin coupled with estimates from the proprietary RMS Caribbean Hurricane Risk Model.[15]

[13] The assumption that only one disaster may occur each year will also be relaxed in the Section "Climate change, adaptation measures and timescales" once we have the empirical loss distribution, but in this section we make a simplified assumption to highlight the cumulative impact of climate change on economic losses.

[14] Based on the results of our simulation, if the climate change time follows exponential distribution with the parameter *1/T*, the tail of the simulated distribution is very close to the worst case scenario, where climate change occurs in the first year. In addition, the mean losses are greater if climate change time is a uniform distribution than if it is an exponential distribution for all scenarios. Thus, the setting of uniform climate change time is practical and closer to the real scenario.

[15] We used the latest release of the RMS Caribbean Hurricane Risk Model in 2011 to assess hurricane risk from the medium-term perspective (5-year forward-looking period) in 25 Caribbean islands and

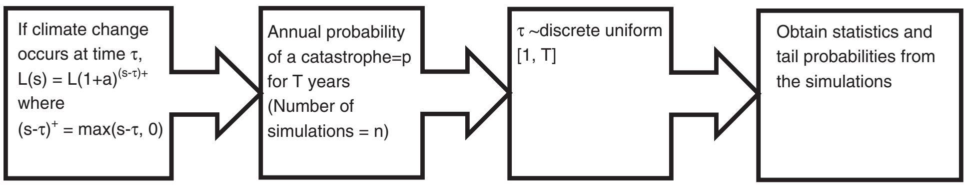

Figure 1. Steps for simulations of the catastrophic risk model.

The cumulative growth effect plays a very important role in capturing the impact of climate change even if this impact is uncertain. For more than a one-year timescale, the aggregate distribution of catastrophic losses with climate change will show a fatter tail compared with the case with no climate change. For example, if we consider a two-year timescale and assume that climate change increases or decreases the loss by b ($b > 0$) per year with an equal probability (1/2), the two-year aggregate distribution of losses will have a fatter tail with climate change since the cumulative impact of the positive value will dominate that of the negative value $((1/2)*(1+b)^2 + (1/2)*(1-b)^2 > 1)$.[16]

The simulation based on this simple model is executed in three steps that are summarised in Figure 1: First, assume that climate change occurs in year τ, $\tau \in [1, 2, \ldots, T]$. The potential loss caused by a catastrophe is specified as $L(s)$, $s=1, \ldots, T$, where $L(s)=L$ for $s \leqslant \tau$ and $L(s)=(1+a)^{s-\tau}L$ for $s > \tau$. Next, the occurrence of a catastrophe is randomly simulated with an annual probability p during the T years for n simulations. Given that climate change occurs in year τ, if a catastrophe occurs in a year s, a catastrophic loss $L(s)$ specified above is assigned; if no catastrophe occurs, then $L=0$. Finally, τ is supposed to follow discrete uniform distribution with parameters $[1, T]$.

The parameters of the benchmark case are as follows: $p=0.01$, $L=1$, $T=20$, $n=10^5$. If there is no climate change, $a=0$, and the other parameters are the same as in the benchmark case, the aggregate loss simply follows a binomial distribution with parameters $T=20$, $p=0.01$. Since we can identify the exact distribution of the aggregate loss, the statistics and tail probabilities can be obtained. However, with climate change

territories, including high-resolution storm surge modelling, region-specific building inventory and component-based vulnerability. The methodology consists of three main steps: stochastic storm-track generation, adding pressure histories to tracks and importance sampling to obtain a manageable number of hurricanes (Michel-Kerjan *et al.*, 2012). In the first step, a Monte Carlo set of storm tracks with associated rates of occurrence is generated using a random-walk technique and calibrated using historical track data. The hurricane frequency and severity are based on historical storms that have struck the Atlantic Basin and coastal regions since 1886. In the second step, pressure histories are added to the tracks using a second random walk technique when the storms are over the ocean. Finally, after generating around 100,000 years of simulated time, tracks with similar paths and intensities at key locations are identified and grouped together. Importance sampling is achieved by retaining a greater proportion of intense storms than weaker storms.

[16] This example can be extended to multiple-year timescales. As long as the probability of positive impact on losses is greater than the probability of negative impact on losses, climate change will lead to a fatter-tail loss distribution.

Table 2 Impact of climate change on the statistics of the simulated losses without adaptation

p=0.01, T=20, L=1			
Climate change factor (a)	*0*	*5%*	*%change*
Expected Value	0.2018	0.2428	20.32
Standard Deviation	0.4482	0.5465	21.93
Skewness	2.2029	2.2903	3.97
Kurtosis	7.7498	8.2858	6.92
VaR (95%)	1	1.442	44.20
VaR (97.5%)	1	1.6533	65.33
VaR (99%)	2	2.3314	16.57
ES (95%)	1.3754	1.8622	35.39
ES (97.5%)	1.7508	2.2166	26.60
ES (99%)	2.107	2.7279	29.47
Prob(Loss > 0.5)	0.1831	0.1835	0.22
Prob(Loss > 1.0)	0.0177	0.1663	839.55
Prob(Loss > 1.5)	0.0177	0.0416	135
Prob(Loss > 2.0)	0.001	0.0165	1,550

impact, that is $a \neq 0$, we have to resort to simulations to explore the statistical properties of the aggregate loss.

After constructing our simple catastrophe risk model, we will examine whether it captures the cumulative effect of climate change on the loss. We will use an arbitrarily set positive climate change factor (a=5 per cent or 0.05) to show its different impacts on the expected loss and the tail of the loss.

Table 2 reports the statistics of the simulated losses without climate change (a=0) and with climate change (a=0.05). These statistics include the expected value, the standard deviation, the skewness, the kurtosis, the Value at Risk (*VaR*) and the Expected Shortfall (*ES*) of the loss. For *VaR* and *ES*, the values with confidence levels of 95 per cent, 97.5 per cent and 99 per cent are presented. *VaR* and *ES* are indicators of the tail of loss distributions. The greater the value of *VaR* or *ES* for the same confidence level, the fatter tail the loss distribution. Value at Risk with confidence level α (VaR_α) denotes the α-percentile of the loss distribution. The proportion of the loss greater than VaR_α is at most $(1-\alpha)$. The formal definition of *VaR* is shown in (1).

$$VaR_\alpha(L) = inf\{l{:}P(L > l) \leqslant 1 - \alpha\}. \tag{1}$$

Expected Shortfall (ES_α) is defined as (2), which is the expected value of the tail of the loss distribution with the loss threshold VaR_α.

$$ES_\alpha(L) = E(l|l \geqslant V\alpha R_\alpha(L)). \tag{2}$$

The advantage of *ES* over *VaR* lies in that *ES* is a coherent risk measure.[17] (The axiom of coherence was proposed by Artzner *et al.* (1997, 1999); *VaR* violates the

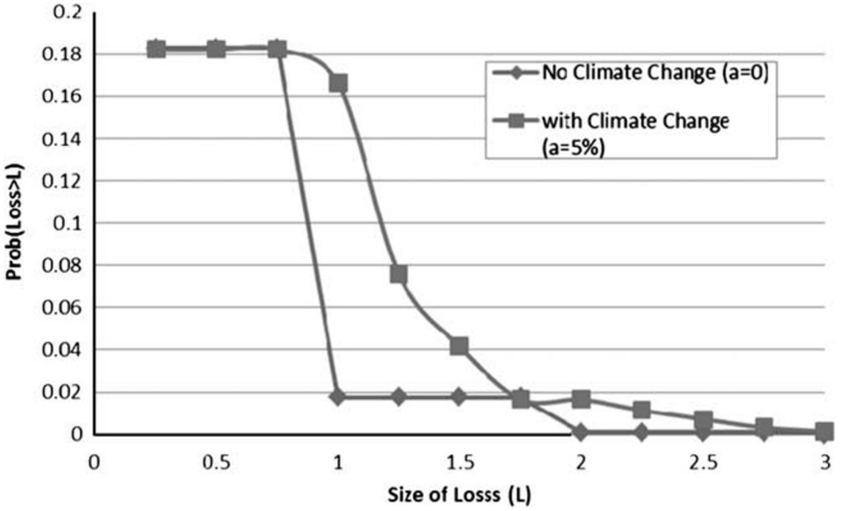

Figure 2. EP curves with and without climate change based on a simple catastrophic risk model.

axiom of subadditivity, thus is not a coherent risk measure. For completeness, we provide both measures.)

In the presence of climate change, the simulated expected loss increases 20.32 per cent while the tail statistics for *ES*s increase by at least by 26.60 per cent. The percentage increase in tail probabilities due to climate change is very significant. For instance, the probability that the 20-year expected loss is greater than the value of the house increases from 1.77 to 16.63 per cent (a 840 per cent increase) with potential changing climate. (The 1-year expected loss per year with no climate change is around 20 per cent of the value of the house). The results are also consistent with what most climate models have shown: It only takes small changes in the mean climate to generate large changes in extreme weather.[18]

Figure 2 depicts the exceedance probability curves (EPs)[19] with cumulative climate change (a=5 per cent) and without it (a=0) based on our simple catastrophic risk model. It reveals the importance of integrating climate change when modelling catastrophic risks to see its impact on the tail of the loss distribution. Climate change produces higher inter-temporal correlations through its cumulative effect over time, which in turn leads to a fatter-tail loss distribution. Owing to the uncertainty associated with climate patterns, there are challenges in estimating the loss distribution, and this could significantly increase the amount of capital insurers and

[17] A risk measure whose domain includes the convex cone is called coherent if it satisfies four axioms: translation invariance, subadditivity, positive homogeneity and monotonicity; McNeil *et al.* (2005).

[18] Wilkins (2010).

[19] For a given portfolio of buildings at risk, the EP is the probability p that a certain level of aggregate loss US\$$L$ will be exceeded in a given year, that is, p=Prob(Loss > L).

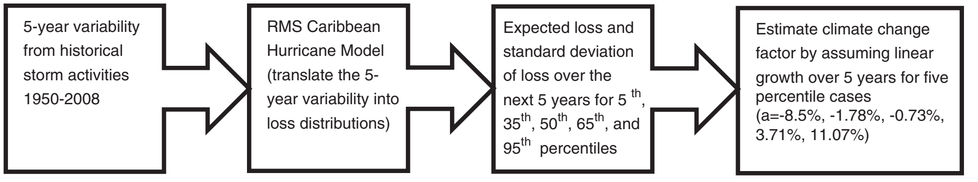

Figure 3. Steps for estimating climate change factor, *a*.

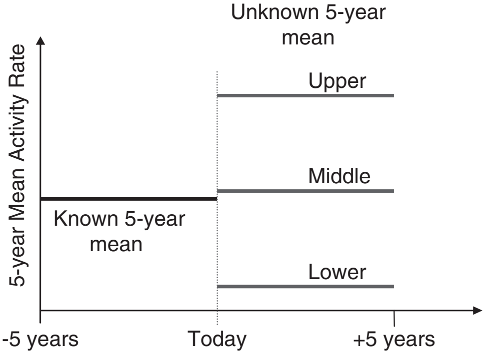

Figure 4. A simple model that estimates the probability and level of storm activity rate based on historical storm activity rate.

reinsurers need to set aside to cover average annual losses and extreme losses. This in turn will depress the supply of insurance.[20]

Estimating climate change factor using historical storm activities and the RMS Caribbean hurricane risk model

Hurricanes often form from June to November in the Caribbean Sea, the subtropical and tropical northern Atlantic Ocean and the Gulf of Mexico, which are collectively referred to as the Atlantic Basin. The most active months for hurricanes are August through October when the Atlantic Basin experiences its peak water temperatures, fuelling storm formation.[21] We will use the storm activities in the Atlantic Basin as an example to illustrate how we calibrated the climate change factor (a) in this area. The steps to estimate the climate change factor from historical climate activities are summarised in Figure 3.

Since the trend in losses due to climate change may not often be easily identified based on historical diagrams, we begin by using a simple 5-year projection model to estimate the growth rate of storm activities in the Atlantic Basin. Figure 4 shows the basic concept: The next 5-year mean activity rate is predicted based on the mean over

[20] Charpentier (2008); Herweijer *et al.* (2009).
[21] Michel-Kerjan *et al.* (2012).

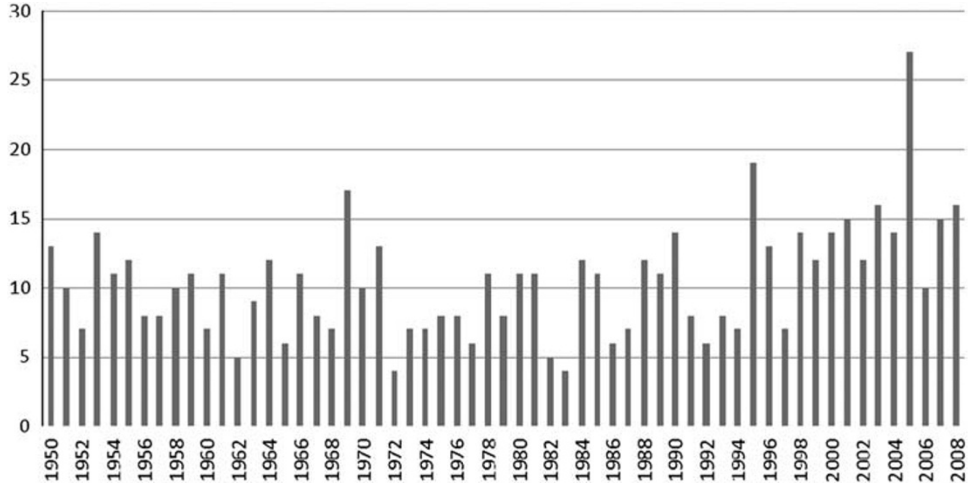

Figure 5. Number of named storms in the Atlantic Basin during 1950–2008.
Source: NOAA.

the past 5 years. This is equivalent to the example that an insurer who issues home insurance predicts the next 5-year average rate based on the past 5-year average rate and the historical growth pattern for the 5-year average rate. "Upper", "Middle" and "Lower" can reflect different percentiles of future storm activity rate. For example, "Upper" can be the 95th percentile, "Middle" can be the median and "Lower" can be the 5th percentile. This model incorporates non-stationarity properties of catastrophic losses into the "medium-term" (5-year) forward-looking view of risk, as indicated in Herweijer *et al.*[22]

Figure 5 shows the annual number of named storms in the Atlantic Basin from 1950 to 2008. Figure 6 focuses specifically on Category 3 to 5 hurricanes on the Saffir-Simpson scale over the same time period. We use this historical storm activity to calculate the average annual storm activities for the previous 5 years. The 5-year average annual activity rates (AAR) are shown in Figures 7 and 8. Figure 7 (Figure 8) presents the activity rates for named storms (Cat 3–5 storms). For instance, the 5-year average annual storm activity rate in 1954 is the average number of storms from 1950 to 1954. According to Figure 5, there are 13, 10, 7, 14, and 11 (12, 8, 8, 10, 11) named storms in the Atlantic Basin from 1950 to 1954 (from 1955 to 1959). Thus, the 5-year AAR in 1954 (1959) is equal to 11 (9.8) named storms in Figure 7. If we take the year 1954 as the base year, the growth rate over the 5-year timescale can be calculated by the growth rate of the 5-year AAR from 1954 to 1959 ((9.8–11)/11=−10.91 per cent). Since there are a total of 59-year time series of storm activities, we have 55-year AARs (from 1954 to 2008) and 50 growth rates of the

[22] Herweijer *et al*. (2009).

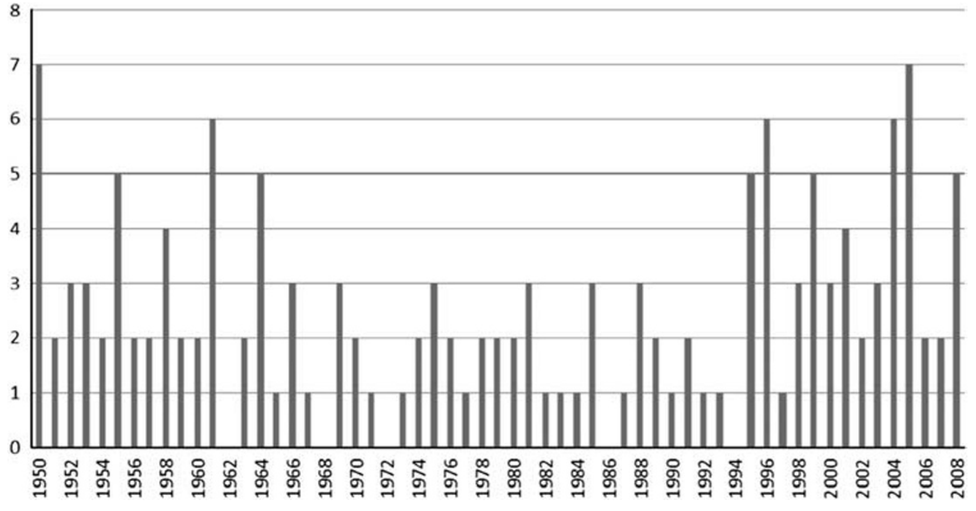

Figure 6. Number of Cat 3–5 storms in the Atlantic Basin during 1950–2008.
Source: NOAA.

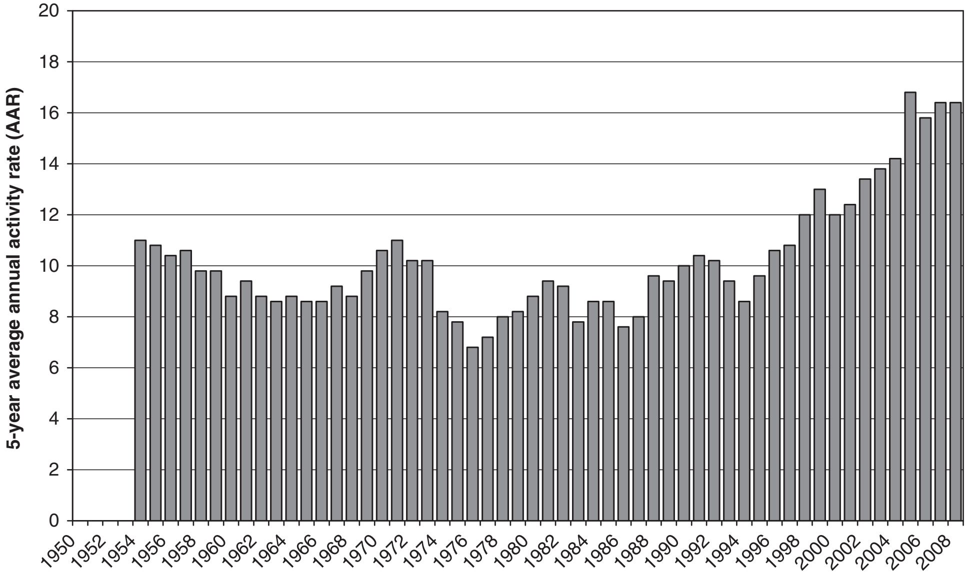

Figure 7. Five-year average annual activity rate based on the number of named storms in the Atlantic Basin from 1950 to 2008.

5-year AAR.[23] Based on these growth rates, the statistics of the variability in storm activity rates can be obtained.

[23] The first growth rate is from 1954 to 1959 and the last growth rate is from 2003 to 2008, with a total 50 growth rates obtained from the 55-year AARs.

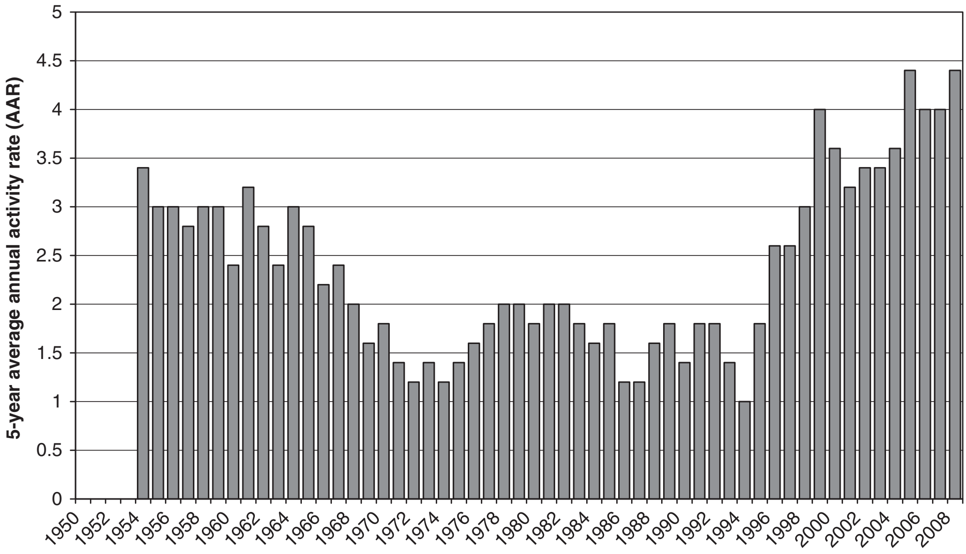

Figure 8. Five-year average annual activity rate in the Atlantic Basin based on the number of Cat 3–5 storms from 1950 to 2008.

Table 3 Statistics of variability in storm activities over successive 5-year periods

Statistics	*All named storms (%)*	*Cat 3–5 Hurricanes (%)*
Mean	6	12
95th percentile	38	85
65th percentile	16	22
50th percentile	5	3
35th percentile	−2	−12
5th percentile	−24	−42

Table 3 exhibits the statistics of variability in storm activities over successive 5-year periods based on all named storms and Cat 3–5 hurricanes. Take the number of Cat 3–5 hurricanes as an example. On average, there is a 12 per cent increase in the number of Cat 3–5 storms between any two successive 5-year periods; 35 per cent of the time we will see a decrease in storm activities of at least 12 per cent, and 35 per cent of the time we will see an increase in storm activity of at least 22 per cent and 30 per cent of the time the change in storm activity is between these two percentages.

These storm AARs are used to adjust the frequencies of individual events in the RMS Caribbean Hurricane Risk Model. We normalise the frequency of all named storms and Cat 3–5 storms relative to the present-day's level in five percentiles. For example, in the 95th percentile, the frequency of all named storms (Cat 3–5 hurricanes) is 38 per cent (85 per cent) higher than the present-day's level. Thus, the frequency of all named storms (Cat 3–5 hurricanes) relative to present day is

Table 4 Percentiles of frequency of storm activities, expected loss, volatility of loss and estimates of climate change factor

	Present day	*Percentiles*				
		5th	*35th*	*50th*	*65th*	*95th*
Frequency of all named storms relative to present-day	1	0.76	0.98	1.05	1.16	1.38
Frequency of Cat 3–5 storms relative to present-day	1	0.58	0.88	1.03	1.22	1.85
Expected loss over 5 years[a]	3,377	2,165	3,086	3,501	4,051	5,707
Standard deviation of loss[a]	9,298	7,326	8,795	9,412	10,117	12,027
Annual growth rate of losses over 5 years[a]	0	−8.50%	−1.78%	0.73%	3.71%	11.07%
Annual growth rate of standard deviation over 5 years	0	−4.66%	−1.11%	0.24%	1.70%	5.28%

[a]The expected loss and standard deviation of loss is for a house with a value of US$100,000.

1.38 (1.85) in the 95th percentile in Table 4. These frequencies are then converted into hurricane loss distributions by the RMS Caribbean Hurricane Risk Model.

Table 4 shows the expected value and the standard deviation of 5-year losses for 5th, 35th, 50th, 65th and 95th percentiles. (These statistics are derived based on changes over successive 5-year periods and the RMS Caribbean Hurricane Risk Model.) We further assume a constant annual growth rate that will be accumulated during 5 years. In each percentile, we can derive this constant annual growth rate based on the same procedures: If the future storm activity is much less severe than the present-day's level (5th percentile), expected losses from hurricanes for a house with a value of US$100,000 (which is consistent with real estate prices in St. Lucia) will decrease from US$3,377 (the present-day expected loss) to US$2,165 in the next 5 years. The annual growth rate of hurricane losses will be −8.5 per cent (US$3,377*$(1+a)^5$=US$2,165, a=−8.5 per cent).

We estimate for five cases of frequency of storms by percentile the climate change factor (or the annual growth rate of expected hurricane losses) in the Atlantic Basin by using a simple 5-year model, historical storm activities and the RMS Caribbean Hurricane Risk Model. Table 4 provides the results. For the 5th percentile, the expected hurricane losses in the Atlantic Basin will decrease by 8.50 per cent. For the 50th percentile, it will increase by 0.73 per cent, and for the 95th percentile, it will increase by 11.07 per cent over five years. In the next section, we will use these five percentile cases as inputs to explore the impact of climate change and adaptation measures on hurricane losses for different timescales.

Climate change, adaptation measures and timescales

St. Lucia is a small Caribbean island close to the Atlantic Basin prone to hurricane risks. Since it has experienced a number of destructive hurricanes, upgrading building codes and strengthening the buildings to withstand hurricane exposures is critical to reducing economic losses.[24] St. Lucia thus provides an ideal natural environment to explore the interplay of climate change and adaptation measures. In this section we simulate the impact of climate change on economic losses with and without risk reduction measures using empirical hurricane loss data in St. Lucia and the five percentiles of climate change factor obtained in the previous section. In the following section we will undertake a series of benefit-cost analyses for these measures.

IIASA, RMS and the Wharton Risk Center analysed the impact of cost-effective adaptation measures on the reduction of losses caused by natural disasters.[21] Their study quantitatively estimated the potential losses and undertook benefit-cost analysis on various adaptation measures in different areas, including hurricane risk in St. Lucia. We use their data on loss distributions, adaptation costs and the impact of four adaptation measures on hurricane risks for different building types.

The detailed characterisations of the four adaptation measures with their estimated costs are summarised as follows.[21]

- *Measure 1: No Adaptation*: No adaptation measure is installed. The total cost is US$0.
- *Measure 2: Roof Upgrade*: This includes the replacement of the roof material with thicker sheeting and tighter screw spacing, as well the use of roof anchors. The total cost of this measure is estimated to be US$9,200.
- *Measure 3: Opening Protection*: This includes strengthening the resistance of windows and doors against wind and heavy pressure. The total cost is estimated to be US$6,720.
- *Measure 4: Roof Upgrade and Opening Protection*: Options 1 and 2 can be combined to provide a more comprehensive level of protection for the structure. The cost for both is estimated at US$15,920.

A wood-frame building in the city of Canaries in St. Lucia is taken as a representative structure. We conduct Monte Carlo simulations to randomly generate the annual EP curve that matches the annual loss to this representative house. The annual EP curve is then incorporated into our model in the Section "A catastrophic risk model with potential climate change impact" to obtain the aggregate 20-year loss distribution for hurricane risk in St. Lucia. We also simulate losses with the four adaptation measures in place.

We first undertake the empirical-based loss simulations with no climate change impact, that is a=0, and then use the median value of a computed in Table 4 (i.e. a=0.73 per cent) to measure the impact of climate change on economic losses. Table 5 shows the impact of climate change on hurricane risk in St. Lucia with roof adaptation measures in place based on these simulations.

Climate change has a greater impact on the tail of the loss than the expected loss even with roof adaptation. In Table 5, the expected loss increases only 1.75 per cent, while the *VaR*s and *ES*s increase by 2.04–2.28 per cent. All the tail probabilities increase by over 4 per cent except for the most extreme tail probability, because roof adaptations eliminate the extreme tail of the hurricane loss. The empirical-based loss simulation results are similar to those based on our catastrophic risk model.

[24] Kairi Consultants Limited (2007).

Table 5 Statistics of simulated losses with *roof adaptation* with and without climate change (d = 5 per cent, T = 20)

a =	*0*	*0.73%*	*% change*
Expected Value	0.3819	0.3886	1.75
Standard Deviation	0.253	0.2583	2.09
Skewness	1.0692	1.0834	1.33
Kurtosis	4.3525	4.4267	1.70
VaR(95%)	0.8658	0.8796	1.59
VaR(97.5%)	0.9901	1.0123	2.24
VaR(99%)	1.152	1.1755	2.04
ES(95%)	1.0406	1.0623	2.09
ES(97.5%)	1.1602	1.1866	2.28
ES(99%)	1.3092	1.3389	2.27
Prob(Loss > 0.5)	0.2763	0.2902	5.03
Prob(Loss > 1.0)	0.0245	0.0266	8.57
Prob(Loss > 1.5)	0.0011	0.0013	18.18
Prob(Loss > 2.0)	0	0	0.00

Note: Here we apply a discount rate (d) of 5 per cent and look at a time period (T) of 20 years.

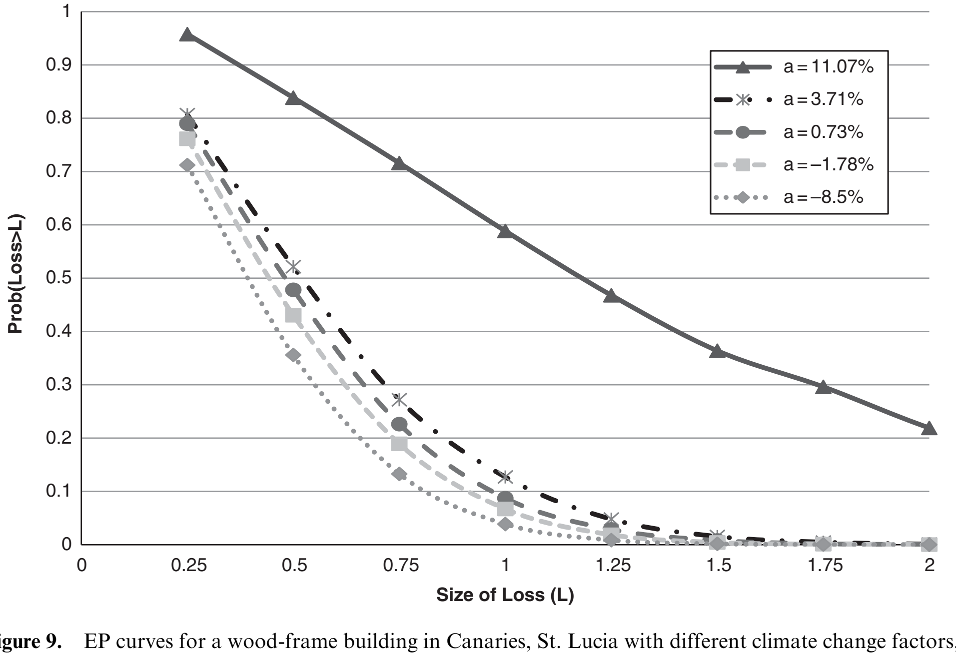

Figure 9. EP curves for a wood-frame building in Canaries, St. Lucia with different climate change factors, no adaptation, T=20, d=5 per cent.

Figures 9–12 depict the EP curves for the wood-frame building in Canaries in 20 years for five climate change factors with the four adaptation measures. The values of the climate change factor are from the five percentiles in the previous

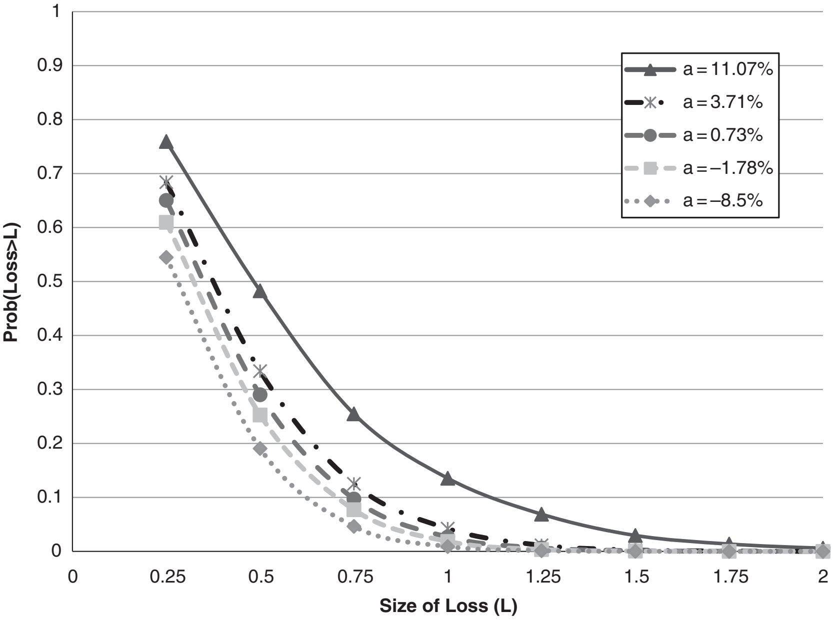

Figure 10. EP curves for a wood-frame building in Canaries, St. Lucia with different climate change factors, roof adaptation, T=20, d=5 per cent.

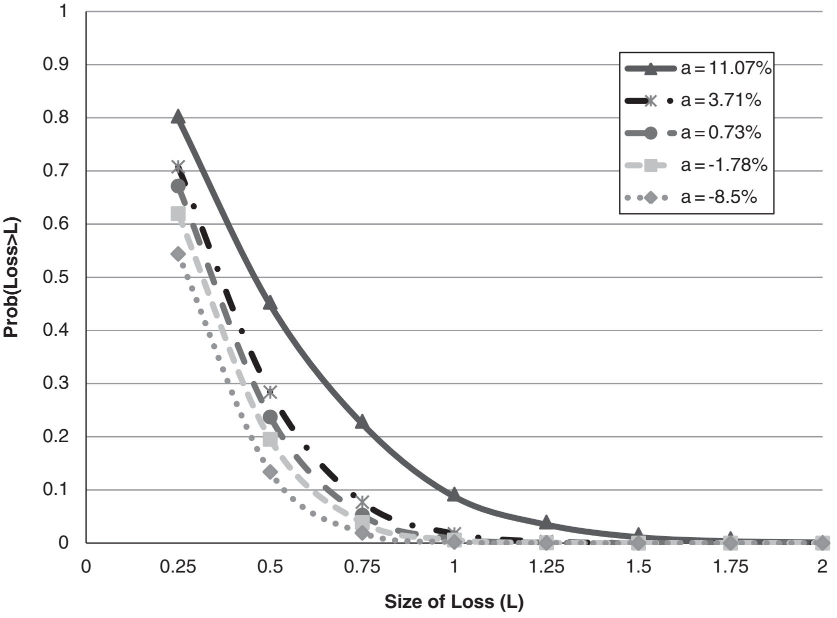

Figure 11. EP curves for a wood-frame building in Canaries, St. Lucia with different climate change factors, opening adaptation, T=20, d=5 per cent.

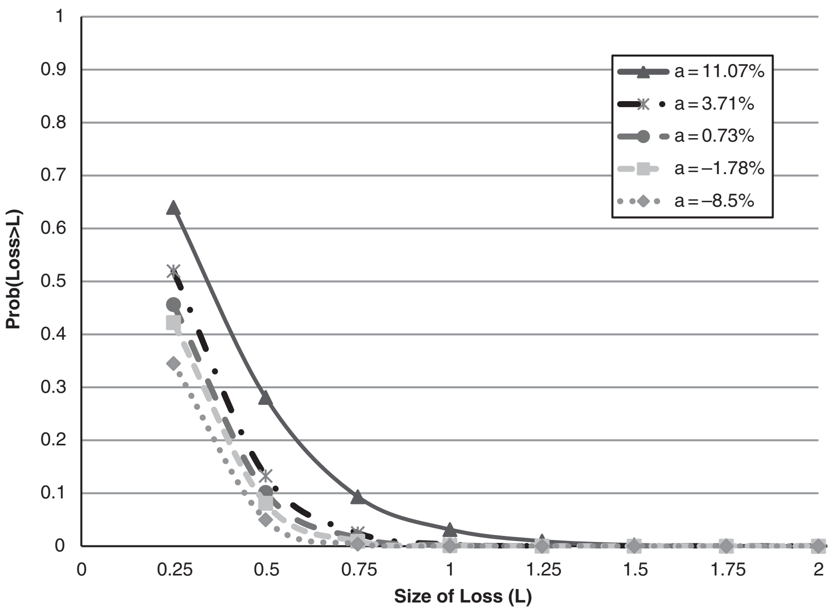

Figure 12. EP curves for a wood-frame building in Canaries, St. Lucia with different climate change factors, roof and opening adaptation, T=20, d=5 per cent.

section: $a_{5\%}=-8.5$ per cent, $a_{35\%}=-1.78$ per cent, $a_{50\%}=0.73$ per cent, $a_{65\%}=3.71$ per cent, $a_{95\%}=11.07$ per cent. As one can see, the higher the value of a, the greater the probability of the expected loss.

For example, in the case of *no adaptation* (Figure 9), the tail probability with threshold 1 (the 20-year expected loss is greater than the value of the house, i.e. $Prob(Loss>1)$) increases from 9 to 13 per cent and further to 59 per cent as a increases from 0.73 to 3.71 per cent and further to 11.07 per cent. Similar patterns can be observed in other figures.

Investing in adaptation measures reduces the variability of the expected loss. For example, with roof adaptation, the range of the EPs with threshold 1 (i.e. $Prob(Loss>1)$) is reduced from 57 per cent (Figure 9) to 13 per cent (Figure 10). This range will be further reduced to 9 per cent with opening adaptation (Figure 11) and to 3 per cent with roof and opening adaptation (Figure 12).

Figures 13 and 14 show the EP curves for the wood-frame building in Canaries for different adaptation measures with a=0.73 per cent (a=11.07 per cent) for the 20-year hurricane losses. The tails of the EP curves are thinner with roof and opening adaptations combined than with opening adaptation, which in turn are thinner with roof adaptation and thinnest with no adaptation. For example, in Figure 14 (a=11.07 per cent), the tail probability with threshold 1 (i.e. $Prob(Loss>1)$) declines from 27 to 14 per cent, to 9 per cent and further to 3 per cent for no adaptation, roof adaptation, opening adaptation and roof and opening adaptation, respectively. Moreover, for a higher climate change factor (a=11.07 per cent), the difference between EPs with and without adaptation is

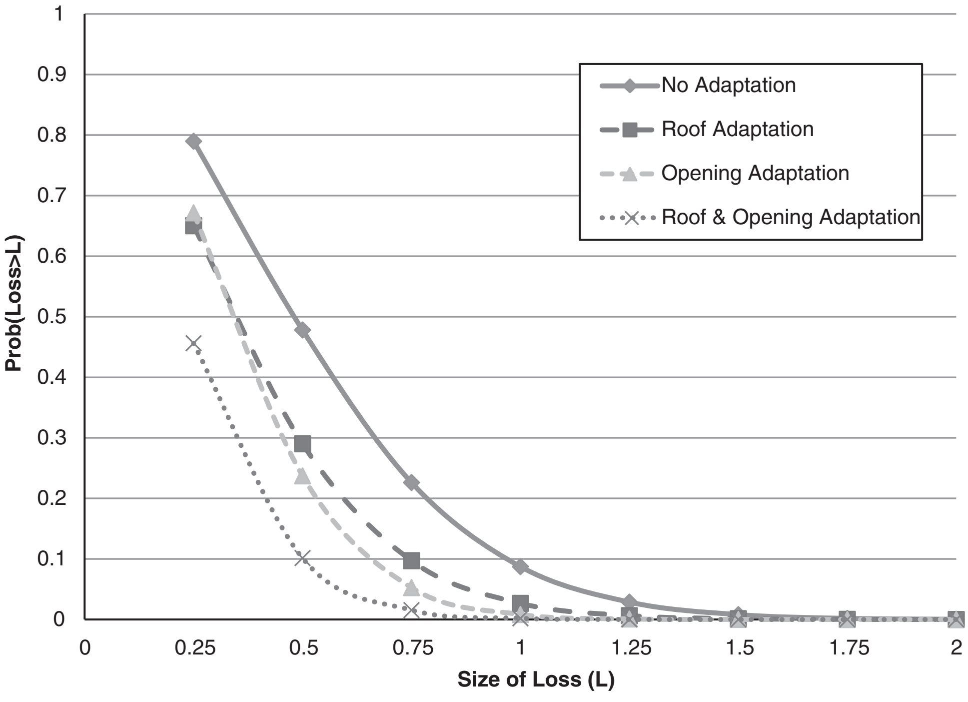

Figure 13. EP curves for a representative wood-frame building in Canaries, St. Lucia with different adaptation measures in place, a=0.73 per cent, T=20, d=5 per cent.

more significant than that for a lower one (a=0.73 per cent), as one would anticipate.

In Figure 13, the tail probability with threshold 1 (i.e. $Prob(Loss > 1)$) with roof and opening adaptation measures in place declines around 8 per cent from that with no adaptation in the median case (a=0.73 per cent). In contrast, in Figure 14, the tail probability with the same threshold with roof and opening adaptation declines around 24 per cent in the 95th percentile case (a=11.07 per cent). These indicate that if climate change has more impact on expected losses, adaptation measures are more important in reducing total risk. Moreover, by comparing the EP curves with timescales of 10 and 20 years, we also observed that the longer timescale, the greater the risk exposure, and thus the fatter tail the loss.[25]

Our results suggest that adaptation will lower expected losses significantly should climate change lead to more devastating hurricanes in the Atlantic Basin in the coming years. To illustrate this point, investing in roof and opening adaptation measures can reduce the tail probability of the hurricane loss three times more in the worst climate scenario (a 24 per cent decline in tail probability loss) compared with the median climate scenario (an 8 per cent decrease due to adaptation). We now turn to whether

[25] The EP curves for 10 years are not shown here but are available from the authors on request.

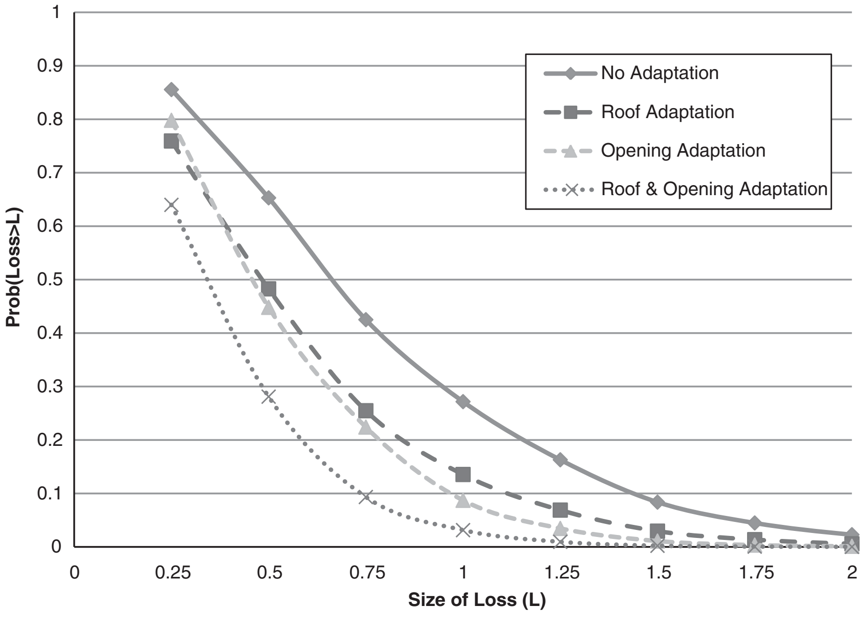

Figure 14. EP curves for a representative wood-frame building in Canaries, St. Lucia with different adaptation measures in place, a=11.07 per cent, T=20, d=5 per cent.

investing in such adaptation measures is cost-effective and, if so, under which conditions.

Quantifying the benefit-cost ratio of risk reduction measures

In this section, we will conduct a benefit-cost analysis on four adaptation measures for a representative wood-frame building in Canaries using simulated hurricane losses in St. Lucia. The benefit from adaptation is defined as the reduction in the expected economic loss with a specific adaptation measure compared with the expected direct physical loss with no adaptation. A standard wood-frame building in Canaries of St. Lucia has a value of US$100,000. Roof upgrade costs US$9,200, opening protection costs US$6,720, and roof and opening adaptation costs US$15,920. These adaptation costs are the cost estimates for adjustments to existing buildings. The costs will be much less for new buildings. With this information and our simulation results for different timescales, Benefit/Cost (B/C) ratios for different adaptation measures can be derived.

Tables 6 and 7 exhibit expected benefits from lowering expected losses from hurricanes over time in relation to the costs for undertaking three adaptation measures. The B/C ratios are computed for time horizons that vary from 5 to 20 years for the wood-frame building in St. Lucia using climate change factors of a=0.73 per cent and a=11.07 per cent, respectively. These time horizons were chosen to show the minimal timescale that makes investing in adaptations financially attractive. We use the same 5 per cent discount rate as before.

Table 6 Benefit/cost ratios of different adaptation measures and time horizons for a wood-frame building in Canaries with a medium climate change factor ($a = 0.73\%$)

Time horizon (years)	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*20*
Benefit from adaptation (reduction in expected losses) (unit = US$100,000)												
Roof adaptation	0.047	0.054	0.062	0.070	0.077	0.083	0.092	0.095	0.103	0.108	0.114	0.139
Opening adaptation	0.057	0.065	0.075	0.082	0.091	0.099	0.107	0.114	0.122	0.128	0.134	0.163
Roof & opening	0.088	0.102	0.117	0.130	0.144	0.156	0.169	0.179	0.191	0.201	0.212	0.256
Adaptation cost (unit = US$100,000)												
Roof adaptation	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092
Opening adaptation	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067
Roof & opening	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159
Benefit/Cost ratio												
Roof adaptation	0.515	0.591	0.678	0.761	0.841	0.900	0.996	**1.037**	1.115	1.175	1.238	1.505
Opening adaptation	0.842	0.973	**1.113**	1.223	1.359	1.470	1.591	1.699	1.810	1.902	1.996	2.426
Roof & opening	0.553	0.641	0.734	0.819	0.904	0.979	**1.064**	1.124	1.201	1.265	1.329	1.611

Note: We bolded the B/C ratios higher than one, indicating when the adaptation measure becomes cost-effective.

Table 7 Benefit/cost ratio of different adaptation measures and time horizons for a wood-frame building in Canaries with a high climate change factor ($a = 11.07\%$)

Time horizon (years)	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*20*
Benefit from adaptation (reduction in expected losses) (unit = US$100,000)												
Roof adaptation	0.052	0.062	0.071	0.080	0.090	0.101	0.108	0.119	0.130	0.139	0.145	0.197
Opening adaptation	0.061	0.073	0.084	0.095	0.107	0.120	0.128	0.141	0.153	0.164	0.173	0.234
Roof & opening	0.096	0.114	0.133	0.149	0.168	0.188	0.203	0.222	0.240	0.258	0.276	0.370
Adaptation cost (unit = US$100,000)												
Roof adaptation	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092	0.092
Opening adaptation	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067
Roof & opening	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159
Benefit/Cost ratio												
Roof adaptation	0.561	0.673	0.773	0.868	0.979	**1.097**	1.171	1.296	1.409	1.507	1.574	2.140
Opening adaptation	0.908	**1.085**	1.253	1.409	1.586	1.778	1.902	2.101	2.277	2.442	2.568	3.475
Roof & opening	0.601	0.714	0.833	0.933	**1.055**	1.183	1.276	1.396	1.509	1.619	1.731	2.323

Note: We bolded the B/C ratios higher than one, indicating the years when the adaptation measure becomes cost-effective.

Based on numerical results in these two tables, the findings are summarised as follows.

- Benefit from roof and opening adaptation is greater than benefit from just opening adaptation, which in turn is greater than benefit from roof adaptation alone. For example, in Table 6, when a=0.73 per cent and T=10 years, the benefit from roof and opening adaptation is US$8,300 (=0.083 × US$100,000), the benefit from opening adaptation is US$9,900 (=0.099 × US$100,000), and benefit from roof adaptation is US$15,600 (=0.156 × US$100,000).

- The B/C ratio also increases with the time horizon, as expected, indicating that it is more financially attractive to invest in adaptations if homeowners engage in long-term thinking. More specifically, the benefit from investing in adaptation accrues over time, while the costs are incurred upfront.

The minimal timescale that makes the investment in adaptations financially attractive (i.e. B/C ratio > 1) decreases if the climate impact is more severe (a increases from 0.73 to 11.07 per cent). It is 2 years for roof adaptation (from 12 years to 10 years) and roof and opening adaptation (from 11 years to 9 years), and 1 year for opening adaptation (from 7 years to 6 years).

These timescale thresholds correspond to the B/C ratios that are highlighted in bold text in Tables 6 and 7. More severe climate change increases the return from adaptations over a given time horizon and decreases the time horizon to make the investment financially attractive. Take installing roof adaptation for 10 years as an example. The adaptation cost is US$9,200. The increase in benefit (reduction in expected losses) changes from US$8,300 to US$10,100 if median climate (a=0.73 per cent) changes to severe climate (a=11.07 per cent). This will increase B/C ratios as well as reduce the timescale threshold. Note that we used a 5 per cent discount rate in this analysis. If we set it at 0 per cent, B/C ratios will be higher than the ratios shown here, but the patterns are quite similar.

We also graphically show the B/C ratios for three adaptation measures over timescales in the median (a=0.73 per cent) and the severe climate case (a=11.07 per cent) in Figures 15 and 16. B/C ratios increase with the timescale in both cases.

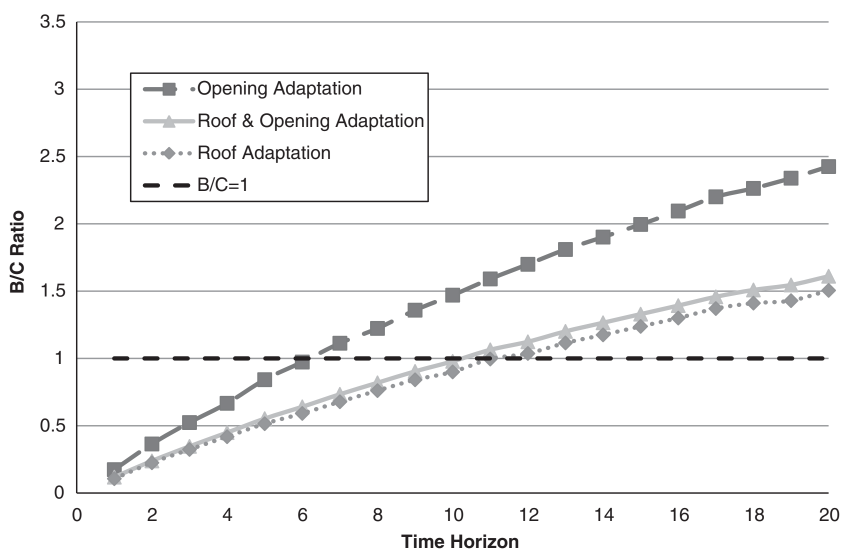

Figure 15. Benefit-cost ratios for a representative wood-frame building in Canaries, d=5 per cent, a=0.73 per cent.

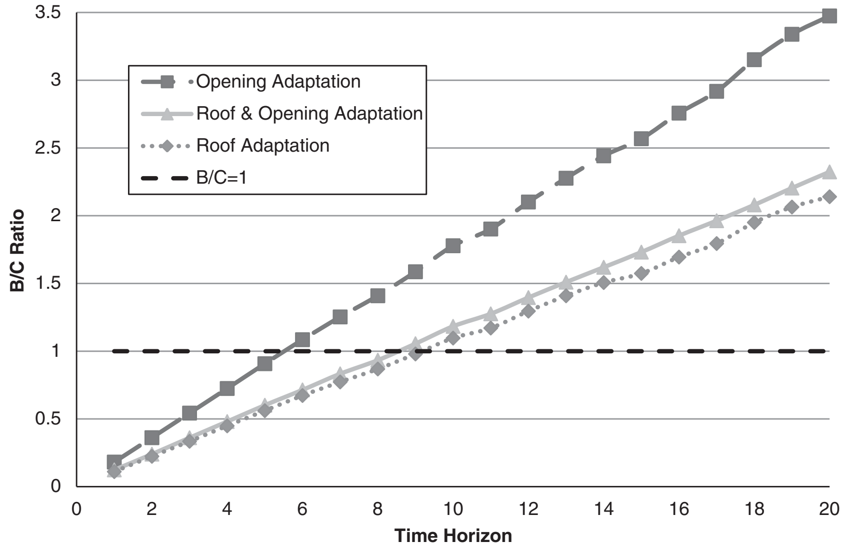

Figure 16. Benefit-cost ratios a representative for wood-frame building in Canaries, d=5 per cent, a=11.07 per cent.

However, they grow faster for the severe case than the median case. This phenomenon is more significant for longer timescales. For the timescale of 20 years, the B/C ratio of opening adaptation is around 3.5 for the severe case, while it is slightly below 2.5 for the median case. The combination effect of the severe climate and a longer timescale enhances the relative benefits of cost-effective adaptation measures. Thus, home-owners should be willing to install adaptations if they anticipate future climate becoming severe and view the benefits of adaptation from a long-term perspective.

Figures 17 and 18 graphically show the synthetic impact of climate change and adaptations on economic losses for two climate cases (a=0.73 per cent and a=11.07 per cent), when the timescale is 20 years and the discount rate=5 per cent. When a=0.73 per cent (Figure 17), the EP curve with no climate change and no adaptation lies in the most upper right. This indicates that in the median climate case, all adaptation measures can offset the impact of climate change. However, when a=11.07 per cent (Figure 18), the EP curve with no climate change and no adaptation is very close to the EP curve with climate change and opening adaptation, while the EP curve with climate change and roof adaptation (roof and opening adaptation) lies in the upper-most right (lower left). The impact of climate change (when a=11.07 per cent) on hurricane losses can be offset by opening adaptation and roof and opening adaptation, but if only roof adaptation is installed, the impact of climate change still dominates. In the severe climate case in St. Lucia, all adaptation measures considered here except roof adaptation can reduce the expected loss to the state of no climate change.

To summarise, we calculated the B/C ratios for four adaptation measures installed in a representative wood-frame building in St. Lucia designed to reduce future hurricane losses. The results indicate that opening adaptation, which strengthens the resistance of windows and doors against wind and heavy pressure, is the most

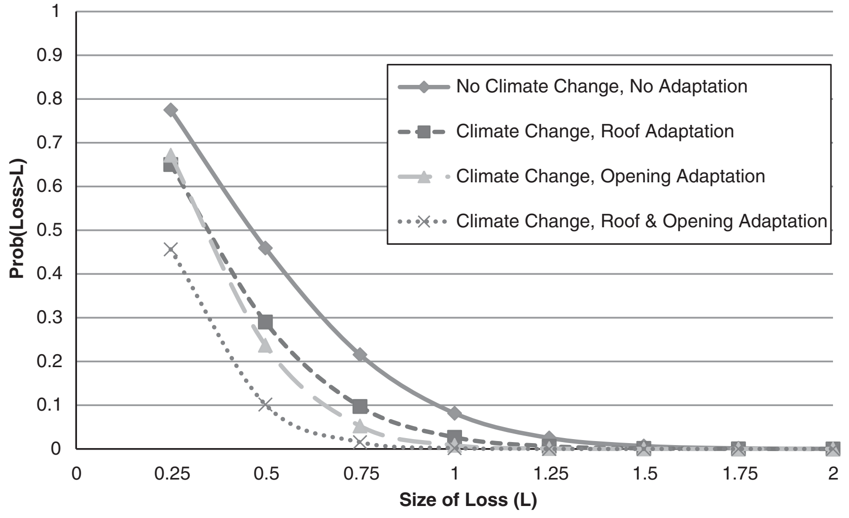

Figure 17. EP curves for a representative wood-frame building in Canaries with no climate change, no adaptation and with climate change different adaptations, a=0.73 per cent, T=20, d=5 per cent.

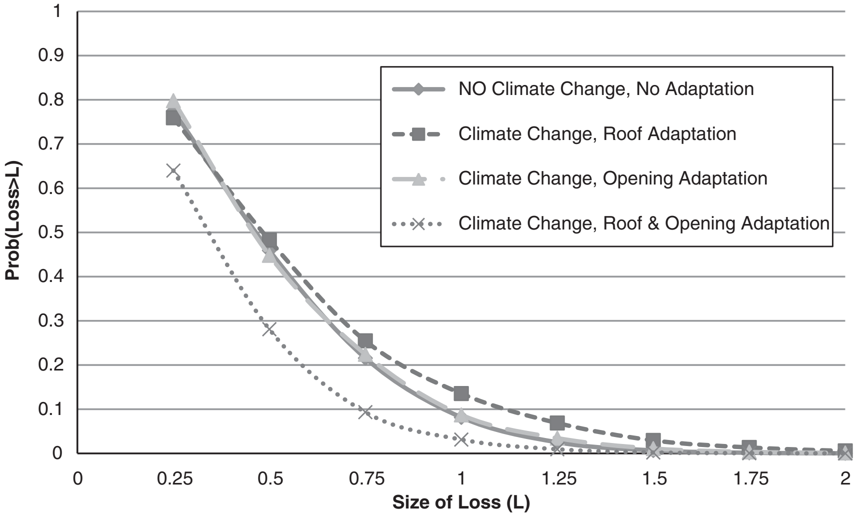

Figure 18. EP curves for a representative wood-frame building in Canaries with no climate change, no adaptation and with climate change different adaptations, a=11.07 per cent, T=20, d=5 per cent.

cost-effective risk reduction measure for this house. Homeowners will find adaptations more financially attractive if they consider hurricane risk for longer timescales, and if they anticipate more severe climate change triggering intensification of hurricane risks in the future. In our severe climate case, all adaptations (except for roof adaptation) would offset the impact of climate change on the expected loss. This has important policy implications in terms of building codes and their enforcement.

Conclusions

This paper uses a simple growth model to quantify the impact of climate change on economic losses from natural hazards. We calibrate this growth model using historical storm activity and determine five percentiles of our climate change factor parameter. The paper then undertakes benefit-cost analyses of four adaptation measures using empirical hurricane risk data in St. Lucia and estimates of climate change impacts on economic losses from the five percentiles of the climate change factor in the Atlantic Basin with and without these risk reduction measures in place for a representative house on the island of St. Lucia. Our results suggest that adaptation measures play a critical role in reducing exposure from future hurricanes there.

According to the benefit-cost analyses of adaptation measures in St. Lucia we have undertaken, homeowners will have more economic incentives to install adaptation measures if they anticipate more extreme climate and consider this investment from a longer timescale perspective. We also found that *opening adaptation* is the most cost-effective adaptation measures for a wood-frame building in St. Lucia. Our approach in the previous section indicates how to choose among different adaptation measures to reduce potential property losses for homeowners. Policymakers thus should encourage the installation of these measures by providing tax deductions and savings on home insurance premiums to reduce the aggregate loss *ex ante* instead of paying for disaster relief *ex post*. An interesting topic to explore in future research is how to share the cost of the risk reduction measures among government (taxpayers), homeowners and insurers.

Future research on the interplay of the impact of adaptation measures and climate change could address the following issues:

- We have assumed that the impact of climate change on economic losses remains the same every year for each climate factor in the benefit-cost analyses on adaptation. However, in reality, this impact may change over time. Uncertain impacts of climate change may lead to more challenges if the structural parameters, such as standard deviation, are also unknown.[26,27]
- Empirical evidence suggests that the proportion of indirect impacts increases in larger disasters, and thus may constitute a larger fraction of total losses and damage in large disasters than in smaller disasters.[28] Taking account of the indirect losses from natural disasters, such as business interruption, unemployment and health expenses stemming from natural hazards may increase the B/C ratio, making investment in adaptation more attractive.

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[26] If standard deviation of a loss distribution is unknown, the moment-generating function of the loss may approach infinity. In this case, we cannot set an upper bound to the expected loss, and the outcomes of benefit-cost analysis will be misleading, ignoring the extreme tail of the loss.

[27] Weitzman (2009).

[28] Gordon and Richardson (1995) and Toyoda (1997).

- Even if we undertake the above analyses with the assumed costs, premium reductions, and adaptation measures, these improvements may not be implemented. For example, building codes are not enforced in St. Lucia, making residents vulnerable to future hurricanes. If we also consider these problems in the analyses, the economic benefit of implementing adaptation measures will be even greater than anticipated.
- Future research can also apply similar approaches to the one used by Dawson *et al*.[29] to evaluate the effectiveness of "non-structural" adaptation measures, such as changes in existing land-use planning, resilient property construction, building codes and insurance policies.

The approach we have used in this paper can analyse economic benefits and costs of adaptation measures in other risk-prone areas if the recent annual loss data and historical adjacent climate-related activities are available. The analyses based on our approach can assist homeowners in making decisions among various risk reduction measures in the face of climate change.

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[29] Dawson *et al*. (2011).

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About the Authors

Chieh Ou-Yang is the Visiting Assistant Professor of the Department of Economics and Finance at City University of Hong Kong. He was a Willis Re Postdoctoral Research Fellow at the Wharton Risk Management and Decision Processes Center. He holds a PhD and MA from the Wharton School, University of Pennsylvania.

Howard C. Kunreuther is the James G. Dinan Professor of Decision Sciences and Business and Public Policy at the Wharton School, and co-director of the Wharton Risk Management and Decision Processes Center. He has a long-standing interest in ways that society can better manage low-probability, high-consequence events. He is a Fellow of the American Association for the Advancement of Science, and a Distinguished Fellow of the Society for Risk Analysis. Recent books are *At War with the Weather* (with E. Michel-Kerjan, 2011); *Learning from Catastrophes* (with M. Useem, 2010); and *Insurance and Behavioral Economics: Improving Decisions in the Most Misunderstood Industry* (with M. Pauly and S. McMorrow, 2013).

Erwann O. Michel-Kerjan is Managing Director of the Wharton School's Center for Risk Management and Decision Processes, and teaches Value Creation in the Wharton MBA program. He has worked extensively on improving financial protection solutions to extreme events, from natural disasters to terrorism and how to strengthen resilience. He is the author of several acclaimed books, including, most recently, *The Irrational Economist* (PublicAffairs Books, with P. Slovic) and *At War with the Weather* (MIT Press, with H. Kunreuther), which received the prestigious Kulp-Wright award for the most influential book on risk management.